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Abstract

This paper develops and tests an equilibrium model for analyzing active fund management with ESG considerations. Sustainable investing incentivizes mutual fund managers to intensify information acquisition, expanding the scope of the active fund industry. Sustainability-guided information and trading decisions result in increasing portfolio deviation from benchmarks at the fund level, while they contribute to enhancing price informativeness and diminishing discount rates at the stock level. Collectively, the negative ESG-expected return relation amplifies for green assets but weakens for brown assets, as supported by evidence from the implied cost of equity capital.

Keywords: ESG, Information acquisition, Mutual funds, Asset pricing
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1 Introduction

The managerial skills of active mutual funds have been a significant area of interest for financial economists. Fund managers are driven to conduct research and gather information to achieve superior performance, enabling them to attract capital flows and gain economic benefits (Berk and Green, 2004; Pástor and Stambaugh, 2012). However, in recent years, the landscape of mutual fund investing has experienced a growing influence of Environmental, Social, and Governance (ESG) considerations. For instance, Hartzmark and Sussman (2019) document that after the initial publication of fund sustainability ratings by Morningstar, high-sustainability funds attracted significant inflows. Mutual fund managers, in turn, have been prompted to adjust their optimal policies for information acquisition and portfolio decisions, aligning more closely with preferences of ESG-perceptive investors. Despite this shift towards sustainable investing, there is limited knowledge regarding the equilibrium implications for mutual funds' information and investment policies, fund performance, the scope of the active fund industry, and the cross-section of asset pricing in the presence of ESG-perceptive intermediaries.

This paper aims to bridge the existing gap by analyzing the equilibrium implications of sustainable investing through a model that builds upon the information acquisition literature (Grossman and Stiglitz, 1980; Hellwig, 1980). The proposed economy encompasses multiple risky assets and a continuum of risk-averse agents. These assets differ in their ESG profiles, ranging from the most sustainable (green) to the least sustainable (brown). The agents exhibit heterogeneity in two aspects: first, their preferences for holding green assets range from ESG indifference to high ESG perceptiveness. Second, each agent can acquire costly signals about the financial payoffs of investable assets, with some agents being more skilled and having a more favorable cost function. In equilibrium, active fund managers are agents who possess a strictly positive amount of private information. On the other hand, for the remaining participants (e.g., households or passive funds), the marginal cost of information exceeds the marginal benefit for all assets, leading them to remain uninformed. We categorize agents with a preference for sustainability above the average preference as ESG-perceptive and those below the average as ESG-indifferent.

The model generates a comprehensive set of predictions for both active funds and individual stocks within the universe. In our initial analysis, we illustrate that a fund's signal precision increases when its ESG preferences diverge from the aggregate, and when the ESG attributes of the underlying assets deviate from green neutrality. Moreover, sustainable investing plays a significant role in fostering the expansion of active fund management. Specifically, ESG-perceptive funds are motivated to gather more information on green assets and less on brown assets. Conversely, ESG-indifferent funds prioritize information acquisition about brown assets and less about green ones. Nonetheless, in equilibrium, there is an overall increase in information acquisition driven by ESG motives. This is because the marginal benefit of information is particularly high when ESG preferences are compatible with the asset sustainability profile.

Considering the expansive scale of the asset management industry (with total assets under management for US domestic equity funds surpassing ten trillion dollars as of December 2023, according to statistics from the Investment Company Institute), the cross-agent aggregation of private signals introduces substantial asset pricing implications. Notably, the informativeness of an asset price varies among individual stocks, exhibiting enhancement for assets held by mutual funds that demonstrate greater dispersion in their ESG preferences. Additionally, assets deviating from the average range of sustainability profiles also exhibit improved price informativeness.

Next, the analysis reveals that mutual funds optimally overweight assets with more precise signals and compatible ESG profiles. Clearly, ESG-perceptive funds tend to overweight green stocks, while ESG-indifferent funds lean towards overweighting brown stocks. However, the model further suggests that the portfolio tilts become more pronounced for stocks with higher signal precision. Combining ESG preferences and information acquisition, the ESG-based portfolio tilts, in turn, result in an increasing deviation of the optimal portfolios from benchmarks. Fund performance is determined by both ESG considerations and managerial skills. As in Pástor et al. (2021), accounting for ESG preferences while excluding skill, a passive ESG-perceptive (ESG-indifferent) fund would deliver a negative (positive) alpha due to overweighting lower (higher) expected return green (brown) stocks. Accounting for skill, the integration of sustainable investing and information decisions leads to nontrivial effects on the optimal strategies of stock holdings, to the extent that the alpha spread between identically skilled ESG-perceptive and ESG-indifferent funds could be nonzero, even controlling for an ESG benchmark that prices passive investments.

To conclude the theory section, the model suggests that information decisions amplify the negative relation between the expected net payoff and the ESG rating for green assets. Specifically, the expected net payoff for green assets is lower primarily due to two forces: (i) the preference for holding green investments, and (ii) the lower posterior variance of the green asset payoff due to higher signal precision. For brown assets, the two forces work in opposite directions. Based on calibration, the positive contribution from the lower valuation of brown assets is likely to surpass the negative effect of information acquisition. In summary, although the ESG-expected return relation is negative and linear in symmetric equilibrium settings, in the presence of asymmetric information the negative relation becomes more (less) pronounced among green (brown) assets.

We empirically test the model based on the universe of actively managed U.S. equity mutual funds and common stocks from 2007 to 2021. We collect monthly firm-level ESG scores from MSCI. We then construct a proxy for fund-level ESG preference based on stock holdings after controlling for a comprehensive list of investment styles.

We confirm the model's prediction that stocks with substantial departure from green neutrality and those held by funds with more heterogeneous ESG preferences display higher price informativeness. To illustrate, a one-standard-deviation increase in the departure from green neutrality (heterogeneity in ESG preferences) is associated with 41.3% (28.4%) higher price informativeness in the next year. The effects are also robust for longer horizons. Thus, sustainable investing not only provides capital to green firms but also improves strong-form market efficiency by incorporating more private information into investment decisions.

The empirical findings support the notion that ESG considerations play an important role in shaping fund managers' information and investment strategies. Specifically, we designate the percentage ownership from funds with high (low) ESG perceptiveness as *Green IO* (*Brown IO*). Since the unobserved signal precision is essentially inversely related to information uncertainty and positively related to information acquisition activities, we focus the analysis on related empirical proxies including idiosyncratic volatility, return volatility, active fund ownership, and analyst coverage.

We demonstrate that mutual fund investments in their preferred ESG domain of stocks vary predictively with levels of information uncertainty. For instance, a one-standard-deviation increase in idiosyncratic volatility is associated with a 25.4% (31.5%) decrease in ESG-Green IO sensitivity (ESG-Brown IO sensitivity). Similarly, a one-standard-deviation increase in active fund ownership corresponds to a 41.0% (81.1%) increase in ESG-Green IO sensitivity (ESG-Brown IO sensitivity). In addition, while the gap between *Green IO* and *Brown IO* increases with stock ESG ratings, the positive ESG-ownership gap relation becomes stronger when information uncertainty declines. Specifically, a one-standard-deviation increase in idiosyncratic volatility (active fund ownership) is associated with 28.4% lower (63.6% higher) ESG-ownership gap sensitivity.

The portfolio tilts associated with ESG-induced information decisions materially affect fund portfolio dispersion and tracking error. We exploit the heterogeneity in information acquisition by analyzing active vs. index funds, finding that ESG-induced portfolio dispersion and tracking error are more prominent among actively managed mutual funds. In particular, a one-standard-deviation increase in the departure of the fund ESG preference from the aggregate preference is associated with 55.7% higher portfolio dispersion and 18.7% higher tracking error among active funds.

We then test the asset pricing implications for individual stocks. While equilibrium theory predicts a negative relation between the ESG rating and *expected* return due to the nonpecuniary benefits of holding green stocks, Pástor et al. (2022) document that U.S. green stocks outperform brown stocks in *realized* returns during the last decade due to an unexpected shift in investors' tastes for green holdings. Therefore, we employ the implied cost of capital (ICC) as a proxy for the expected return. We first confirm that the overall ESG-ICC relation exhibits concavity, with the ESG-ICC relation being more negative among greener stocks and less negative among browner stocks. Next, using *Green IO* as a proxy for the information acquisition intensity for green stocks, we sort stocks into portfolios first by *Green IO* and then by stock ESG rating. We find that the negative ESG-ICC relation is more pronounced among stocks with high *Green IO*, because information acquisition makes the investment in green stocks less risky, lowering their expected returns. When *Green IO* is high, green stocks display a significant 0.115% lower ICC per month than brown stocks. When *Green IO* is low, the ICCs for green stocks and brown stocks are no longer significantly different.

In a similar double-sort setting, first by *Brown IO* and then by stock ESG rating, we document a significantly negative ESG-ICC relation among stocks with low *Brown IO*. When *Brown IO* is low, green stocks display 0.138% lower ICC per month than brown stocks. When brown fund ownership is high, the ICCs for green and brown stocks are no longer significantly different. Our findings remain robust when considering alternative risk-adjusted and characteristic-adjusted ICCs. In summary, the empirical evidence aligns with the model's prediction that information decisions amplify (diminish) the negative ESG-expected return relation for green (brown) assets.

The overall empirical evidence upholds the idea that asset managers indeed integrate ESG factors into their decision-making processes concerning information and portfolio policies. These considerations significantly influence the cross-section of asset prices and the informativeness of prices within the financial market.

Beyond the empirical tests, in the Online Appendix we conduct calibration exercises to further quantify the model implications. We show that an ESG-perceptive fund encounters a large utility loss if forced to adopt the information decision and portfolio strategy that are optimal for an ESG-indifferent fund. This loss is exclusively attributed to the preference for sustainable investing. Second, by using the industry-wide information acquisition cost as a proxy for the size of the active fund industry, we find that the total information cost increases considerably due to ESG motives. Scaling the growth in ESG-induced information by the vast scope of active fund management, the implications of sustainable investing are economically significant. Looking forward, the scope of active funds could further grow with greater dispersion in the sustainability profiles of investable assets and in the preferences for sustainable investing.

This paper contributes to several strands of the literature. First, we further develop the information acquisition literature. Grossman and Stiglitz (1980) consider informed and uninformed agents who trade for their own accounts. Ross (2005) recognizes the possibility that the informed could offer wealth management services to the uninformed. That insight is adopted by Garcia and Vanden (2009), Gârleanu and Pedersen (2018), and Breugem and Buss (2019). Our framework is related to Kacperczyk et al. (2016), who study the rational attention allocation of mutual funds. However, there are significant differences in the overall model and focus. In our setting, information is costly to acquire while equilibrium obtains when the marginal cost of information equals the marginal benefit. This avoids corner solutions where private information is concentrated in few assets. Moreover, we pay special attention to the implications of ESG motives for the active fund industry, the price informativeness, and the intermediary cross-sectional asset pricing.

Second, the paper responds to the growing literature on the asset pricing implications of sustainable investing. While theoretical work makes the premise that ESG-perceptive investors are willing to sacrifice financial payoffs for nonpecuniary benefits (e.g., Pástor et al., 2021; Pedersen et al., 2021; Avramov et al., 2022), there is mixed empirical evidence based on different ESG proxies (e.g., Gompers et al., 2003; Edmans, 2011; Bolton and Kacperczyk, 2021; Pedersen et al., 2021; Bolton and Kacperczyk, 2023).[1] Our model identifies a novel effect of sustainable investing: green firms can benefit from a lower cost of capital due to (i) the nonpecuniary benefits of holding green stocks, as proposed in prior literature and (ii) lower risk due to the information acquired by ESG-perceptive funds. In contrast, the two forces work in opposite directions for brown firms. Therefore, while the ESG-expected return relation is negative and linear in symmetric equilibrium settings, this relation becomes concave in the presence of asymmetric information. Our empirical results confirm this prediction.[2]

[1]A large body of empirical work further studies the effects of corporate sustainability practices along several dimensions, such as firm performance (Lins et al., 2017), environmental impact (Ben-David et al., 2021), and executive compensation (Hazarika et al., 2023).

[2]In an independent work, Goldstein et al. (2024) theoretically study the asset pricing equilibrium when agents with ESG preferences trade a single risky asset characterized by uncertain financial payoff and sustainability profile. In their model setup, investors can access comparable sets of financial and ESG information but have different preferences. Here, we consider agents with different degrees of skills and varying preferences to hold green stocks, who trade multiple assets that differ in their ESG attributes. In addition, we provide a rich set of predictions for the asset management industry including their portfolio choices, expected performance, and industry size. We also implement extensive empirical tests and calibration experiments to highlight the equilibrium implications of ESG considerations for the cross-section of mutual funds and individual stocks.

Third, the paper relates to recent work on sustainable investing by institutional investors (e.g., Amel-Zadeh and Serafeim, 2018; Dyck et al., 2019; Starks, 2023; Oehmke and Opp, 2024). While the existing body of work predominantly centers on ESG scores as the driving force behind sustainable investing, we contribute to this line of research by examining the departure of asset ESG attributes from green neutrality, the departure of fund ESG preference from the aggregate, and the heterogeneity in both asset ESG attributes and fund ESG preferences. These factors are inherently motivated in equilibrium and are substantiated through empirical tests conducted on a comprehensive sample of active funds and individual stocks. Moreover, our findings shed light on the recent debate on whether and how ESG should be incorporated into investment decisions.[3] We show that fund managers could optimally make information and investment decisions based on financial and social objectives, and skilled managers with social motives could still outperform less skilled ESG-indifferent managers. Importantly, ESG motives create a positive externality by enhancing information acquisition and price informativeness of the financial market.

The remainder of this paper proceeds as follows. Section 2 presents the model. Section 3 describes the data. Sections 4, 5, and 6 empirically examine the model's predictions for the stock price informativeness, mutual fund investments, and the cross-section of asset prices, respectively. The conclusion follows in Section 7.

2 Model

2.1 The economy

We begin with describing the supply side of the economy, which involves N investable risky assets whose payoffs load on risk factors. The payoffs of these assets can be

[3]For instance, effective from January 2021, the US Department of Labor (DOL) adopted amendments to the "investment duties" regulation under the Employee Retirement Income Security Act (ERISA). The amendments require retirement plan fiduciaries to "select investments and investment courses of action based solely on financial considerations relevant to the risk-adjusted economic value of a particular investment or investment course of action." See, https://www.federalregister.gov/documents/2020/11/13/2020-24515/financial-factors-in-selecting-plan-investments, for details.

expressed as

$$\begin{cases} f_i = \mu_i + b_i z_N + z_i, \quad i \in \{1, \dots, N-1\} \\ f_N = \mu_N + z_N, \end{cases} \tag{1}$$

where f_i represents the realized payoff of the i-th asset, μ_i is the expected value of the payoff, and z_i is the corresponding (demeaned) risk factor payoff. The N-th security represents an aggregate asset with a payoff that is driven solely by the aggregate risk factor, where the mean payoff is denoted by μ_N, and the shock is represented by z_N. The slope coefficient b_i stands for the asset's exposure to the aggregate risk factor. It is assumed that the shocks are uncorrelated and adhere to a normal distribution. Specifically, $z_i \sim \mathcal{N}(0, \sigma_i)$ for both the individual and aggregate assets. Decisions regarding information are made for the risk factor payoffs, a framework reminiscent of the approach by Kacperczyk et al. (2016).

The risk factor supply is modeled as $\bar{\mathcal{X}}_i + \mathcal{X}_i$, where $\bar{\mathcal{X}}_i$ is the mean supply and $\mathcal{X}_i$ is assumed to follow the normal distribution, specifically, $\mathcal{X}_i \sim \mathcal{N}(0, \sigma_{\mathcal{X}})$. The inclusion of random supply aims to prevent asset prices from fully revealing private signals, resulting in a discrepancy in asset valuations among agents. This can be attributed to the presence of noise traders, trading driven by life-cycle liquidity forces, and the lack of perfect knowledge of the market structure (see Admati, 1985). Then, the implied supply of the investable assets is given by $\bar{x}_i + x_i$, where $\bar{x}_i = \bar{\mathcal{X}}_i - b_i \bar{\mathcal{X}}_N$ is the mean supply and x_i is a random draw from the normal distribution with zero mean and variance equal to $\sigma_{\mathcal{X}}(1 + b_i^2)$. To simplify notations, the gross interest rate and the mean supply of each of the risk factors are all normalized to unity. For a generic interest rate and mean supplies, please refer to the Online Appendix A.

When considering sustainable investing, each risky asset has exogenous ESG attributes represented by the score g_i, which is known to market participants. Assets can be categorized as green or brown based on their positive or negative ESG scores, respectively. While the terms green and brown are often used to characterize environmental externalities, in this paper we follow Pástor et al. (2021) in referring to assets with high overall sustainability profiles as green and those with low profiles as brown. We assume a green-neutral aggregate asset, i.e., $g_N = 0$. This implies that the ESG score of the i-th risk factor is the same as that of the i-th risky asset. In reality, the true color of the market is unobservable, and corporate ESG ratings are ordinal in nature. Therefore, it is innocuous to assume that the aggregate asset represents the cutoff between green and brown investments. To examine the implications of sustainable investing, we do not currently account for potential dependencies between the asset's ESG score and other attributes associated with predicting cross-sectional expected returns, such as market capitalization and value, while this assumption may be relaxed in future work.

On the demand side, we assume that the economy is composed of a continuum of risk-averse optimizing agents indexed by j. As we will demonstrate later in the text, some of these agents are active funds, while others are passive funds or households. Each agent is able to purchase up to N costly signals regarding the random risk factor payoffs in equilibrium. A signal for an asset-agent pair is modeled as

$$\eta_{ij} = z_i + \varepsilon_{ij}, \qquad \varepsilon_{ij} \sim \mathcal{N}\left(0, S_{ij}^{-1}\right), \tag{2}$$

where S_{ij} denotes the signal precision of risk factor i, optimally selected by agent j. Following the literature, the cross-agent average of ε_{ij} is assumed to be zero for each of the risk factors.

The model assumes that, conditional on the realizations of the signals, η_{ij}, individual agents have mean-variance preferences represented by the following equation:

$$U_{2j} = \mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j G_j, \tag{3}$$

where $\mathrm{E}_{2j}[.]$ and $\mathrm{Var}_{2j}[.]$ denote the expectation and variance, respectively, conditional on the signals realized for agent j. The agent's terminal wealth is represented by $W_j = W_{0j} + \sum_{i=1}^{N} q_{ij}\left(f_i - p_i\right) - \sum_{i=1}^{N} c_{ij}\left(S_{ij}\right)$, where p_i is the price of the risky asset, q_{ij} is the portfolio position for the asset-agent pair, and $\sum_{i=1}^{N} c_{ij}\left(S_{ij}\right)$ is the total cost of information acquisition, with $c_{ij}\left(S_{ij}\right)$ denoting the cost per risk factor i. The risk aversion parameter, ρ, is equal across agents. The parameter δ_j is agent-specific and reflects the preference for holding sustainable assets. A higher value of δ_j indicates a stronger preference for sustainable assets, whereas a lower value indicates a weaker preference. The ESG preference parameter is assumed to be non-negative and strictly positive for a non-zero measure of the agents in the economy. Empirically, the fraction of sustainability-perceptive intermediaries is considerable, as shown, for example, by Hartzmark and Sussman (2019) and Geczy et al. (2021). The ESG score of the portfolio is denoted by $G_j = \sum_{i=1}^{N} q_{ij} g_i$. The nonpecuniary benefits from ESG investing are represented by the product of agent-specific preference for ESG investing and the portfolio color, $\delta_j G_j$.[4]

Nonpecuniary benefits in sustainable investing are agent-specific due to the heterogeneity in preferences for ESG investments and signal precision, which both result in unique optimal portfolio policies. The expectation operator comes into play as portfolio weights are based on random signals and asset supplies. Holding green assets increases the utility of agents who prioritize ESG concerns ($\delta_j > 0$), while agents who are indifferent towards sustainability ($\delta_j = 0$) have the standard mean-variance utility, as they do not perceive any nonpecuniary benefit (loss) for holding a green (brown) portfolio.

The equilibrium results we derive below are essentially contingent on the specific form of preferences, which extends the canonical mean-variance framework to include sustainable investing preferences. This set of preferences was originally proposed by Pástor et al. (2021) and Pedersen et al. (2021), and has been subsequently adopted by Goldstein et al. (2024), among others. The variation in ESG preferences across agents is in line with the findings of Avramov et al. (2022), who showed that norm-constrained institutions like pension funds tend to favor green stocks, while hedge funds tend to invest more heavily in brown stocks.

The inclusion of preferences for sustainable investing introduces a dual interpretation into the asset pricing model (see, Pástor et al., 2021). The initial interpretation involves the presence of alpha within a CAPM framework, where alpha does not signify mispricing but rather reflects the non-monetary advantages associated with holding sustainable stocks. The second interpretation entails the emergence of an ESG-type factor, wherein less sustainable firms exhibit more substantial risk load-

[4]As ESG ratings are defined only in relative terms, the scales of ESG preferences δ_j and scores g_i offer a degree of freedom in their choice, as these two quantities appear solely as a product in the agent's preferences. Consequently, any combination of scales that yields the same product $\delta_j g_i$ is equivalent from a pricing perspective, as it provides the same nonpecuniary benefits to the agent. In the calibration exercise detailed in Online Appendix B, we provide a rationale for the choice of parameter values.

ings due to adverse effects of climate changes and regulatory requirements among others. In this context, Engle et al. (2020) have devised factor-mimicking portfolios specifically designed to hedge against climate change news. Our specification of preferences accommodates both interpretations.

We move on to modeling the cost of acquiring information. The cost function, denoted as $c_{ij}(s)$, is a continuous function of the non-negative signal precision $s \geq 0$, where $c_{ij}(0) = 0$. Consistent with Verrecchia (1982) and Breugem and Buss (2019), we assume that the cost is increasing and convex in the signal precision, reflecting the stock-picking abilities of the agent, where a lower cost represents better skills.

The cost function is agent-specific because different agents may possess varying degrees of information processing skills. This is supported by empirical evidence (e.g., Chevalier and Ellison, 1999; Gerakos et al., 2021) and considered in the equilibrium setting of Gârleanu and Pedersen (2018). The cost is also stock-specific, which is consistent with the notion that fund managers can gain informational advantages about specific assets through industry expertise (e.g., Avramov and Wermers, 2006), information flows within financial conglomerates (Irvine et al., 2006; Massa and Rehman, 2008), social connections (Cohen et al., 2008), and geographic proximity (Sialm et al., 2020). With regard to sustainable investing, we remain agnostic about any potential dependencies of the information cost (or managerial skill) on the fund's tendency to hold green assets or on the ESG profile of an investable asset in the absence of compelling evidence.

The model involves a sequence of actions and realizations spanning four periods, although the overall setting is static. In the initial period (period 0), agents are endowed with both initial wealth and the cost function. In period 1, each agent makes an information acquisition decision that determines the precision of multiple signals with respect to the risk factor payoffs. The decision depends on the agent-specific cost function, preference for holding sustainable assets, and the ESG profile of the particular asset. At the end of period 1, signals are realized. In period 2, optimal portfolios are formed based on moments that condition on the signals, and the asset prices and trading volumes are set. Finally, in period 3, asset payoffs are delivered, and utilities are realized.

Our study contributes to the literature on information acquisition in the context of multiple securities. First, by incorporating the cost function, the model internally determines the precision of signals by ensuring that the marginal benefit of information acquisition is balanced with the marginal cost of extracting information. This approach helps preventing the concentration of all information efforts on a single security. Moreover, the framework enables one to examine the impact of ESG motives on various aspects, such as the informativeness of asset prices, signal precision of funds, tracking error, performance, the cross-section of intermediary-based asset prices, and the scope of the active fund industry.

2.2 Active management when ESG matters

The equilibrium prices and optimal signal precisions are derived by backward induction. First, we formulate the portfolio allocation in period 2, conditional on the signals realized in period 1. Then, we solve for the information acquisition decisions in period 1.

In period 2, each optimizing agent observes the realized signals, η_{ij}, and selects the portfolio that, subject to the budget constraint, maximizes the mean-variance utility function in Equation (3). Market clearing determines the asset prices represented in the following proposition, as proven in Online Appendix A.1.

Proposition 1. *The price of a risky asset is given by*

$$p_i = \underbrace{\mu_i + \zeta_i z_i + b_i \zeta_N z_N - \rho\left(\bar{\sigma}_i + b_i \bar{\sigma}_N\right)}_{\textit{cross-agent risk-adjusted posterior payoff}} - \underbrace{\rho\left(\frac{\zeta_i}{\bar{S}_i} x_i + b_i\left(\frac{\zeta_i}{\bar{S}_i} + \frac{\zeta_N}{\bar{S}_N}\right) x_N\right)}_{\textit{random supply component}} + \underbrace{\bar{\delta}_i g_i}_{\substack{\textit{nonpecuniary}\\ \textit{motives}}}, \tag{4}$$

where $\bar{S}_i = \int_j S_{ij}\mathrm{d}j$ represents the cross-agent average signal precision per risk factor i, $\bar{\delta}_i = \bar{\sigma}_i \int_j \hat{\sigma}_{ij}^{-1}\delta_j \mathrm{d}j$ is the aggregate asset-specific ESG preference, $\hat{\sigma}_{ij}^{-1} = \sigma_i^{-1} + S_{ij} + \sigma_{pi}^{-1}$ stands for posterior payoff precision, as perceived by agent j, $\bar{\sigma}_i^{-1} = \sigma_i^{-1} + \bar{S}_i + \sigma_{pi}^{-1}$ is the corresponding cross-agent average, $\zeta_i = \frac{\bar{S}_i + \sigma_{pi}^{-1}}{\bar{\sigma}_i^{-1}}$ is the fraction of the posterior payoff precision attributed to the price and private signals, and $\sigma_{pi}^{-1} = \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}}}$ is the precision of the price signal.

The asset price increases with the cross-agent posterior payoff, adjusted for risk, while it diminishes with the random supplies of the asset-specific and aggregate risk factors. When considering sustainable investing, the green (brown) asset price rises (falls) with the nonpecuniary motives. Indeed, the stock ESG profile and the preferences for holding green assets are important determinants of the cross-section of asset prices, which we comprehensively analyze in Subsection 2.4. At this stage, we focus on understanding active management when ESG matters.

We proceed by deriving the optimal information decisions. In period 1, each agent chooses the precision of multiple signals to maximize

$$U_{1j} = \mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j G_j\right]. \tag{5}$$

The proposition below, which we prove in Online Appendix A.2, describes the signal precision for the asset-agent pair that maximizes the expected utility in period 1.

Proposition 2. *The optimal signal precision S_{ij} is given by*

$$S_{ij} = \max\left[0, s | c'_{ij}\left(s\right) = \psi_{ij}\right], \tag{6}$$

where the pre-cost marginal benefit of information acquisition is

$$\psi_{ij} = \frac{1}{2\rho}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)g_i\right)^2\right). \tag{7}$$

Equilibrium information decisions are derived by solving a fixed-point problem. The precision of the signal in Equation (6) is determined by the marginal benefit of information in Equation (7), which, in turn, depends on the overall signal precision via $\bar{S}_i$, $\bar{\sigma}_i$, and $\bar{\delta}_i$.

For some agents, the equilibrium marginal benefit exceeds the marginal cost of buying an infinitesimal unit of information, $c'_{ij}\left(S_{ij}\right)$, for at least one risk factor. These agents would purchase a strictly positive amount of information, inversely associated with the convexity of their cost function. For other agents, the benefit-cost gap is nonpositive for all risk factors. These agents remain uninformed. The agents purchasing information are active mutual funds, while the uninformed are households or passive mutual funds.

As evident from Equations (6) and (7), beyond the essential (positive) dependence of the signal precision on managerial skills, information decisions also vary with the asset sustainability profile, as well as with the individual and aggregate preferences for sustainable investing. ESG motives come into play through the $\left(\delta_j - \bar{\delta}_i\right) g_i$ term in Equation (7).

Intuitively, mutual funds that are more ESG perceptive than the average $(\delta_j > \bar{\delta}_i)$ attribute higher valuations to green assets. Thus, they would make information decisions to improve their knowledge about green asset payoffs. Conversely, funds that are less ESG perceptive than the average $(\delta_j < \bar{\delta}_i)$ would be reluctant to pay the extra premium associated with green investing. Thus, they are likely to specialize in brown stocks, which incentivizes costly searches for brown asset payoffs. It is important to note that, in Equation (7), ESG motives represent an incremental contribution to the marginal benefit of signal precision, which also depends on risk-based components that would exist even in the absence of sustainability considerations. For this reason, while a fund tilts the attention towards assets with compatible ESG profiles, it could still be exposed to and acquire signals on other assets for diversification.[5]

For a given asset, funds with compatible ESG preferences acquire more precise signals, while funds with incompatible ESG preferences have lower signal precision. Then, a central question emerges: what is the overall impact of an asset's ESG profile on the total amount of information acquired for that asset? Focusing on a green asset, the benefit from information acquisition grows in ESG preferences for two reasons. The first is because of the increasing nonpecuniary benefits from holding the asset, while the second reflects the corresponding growing optimal portfolio position. For a brown asset, both forces imply a benefit from information acquisition that decreases in ESG preferences.[6] The overall effects for both green and brown assets are amplified

[5]Similar to Van Nieuwerburgh and Veldkamp (2010), we find that investors acquire more information about assets they expect to be more exposed to. However, in our framework, agents can still gather information on other assets, as the signal precision optimally depends on the cost of information acquisition, rather than being restricted by a fixed capacity constraint. This further allows us to examine the impact of ESG preferences on the overall price informativeness and the size of the active fund industry.

[6]The sensitivity of the marginal benefit of information acquisition to ESG preferences is

$$\frac{\partial \psi_{ij}}{\partial \delta_j} = \frac{1}{\rho} g_i \left(\rho \bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right) g_i\right).$$

The relation is monotonic provided that the term $\rho \bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right) g_i$ is positive, i.e., when the with larger departure from green neutrality. Taken together, the marginal benefit of signal precision grows quadratically in the product of (i) the departure of agent's ESG preferences from the average and (ii) the departure of the asset from green neutrality. The nonlinearity carries important implications upon aggregating across agents.

In particular, to distill the effect of ESG motives on the aggregate signal precision, in the remainder of this subsection we control for cross-fund managerial skills by considering the cost function $c_{ij}(s) = \kappa s^2$ with $\kappa > 0$. That is, the cost of information is uniform across stocks and agents and it is proportional to the square of the signal precision. This maintains the convexity assumption. The proposition below, derived in Online Appendix A.3, describes the signal precision variation with the ESG profile.

Proposition 3. *The sensitivity of the cross-agent average signal precision, defined in Proposition 1, to the departure of the asset ESG score from green neutrality, $|g_i|$, is given by*

$$\frac{\partial \bar{S}_i}{\partial |g_i|} = \xi_{Ai} \sigma_\delta |g_i| , \tag{8}$$

where $\xi_{Ai} = \left(\rho\kappa + \left(\left(\rho^2 (1 + \sigma_{\mathcal{X}}) + \bar{S}_i\right) \left(1 + \frac{2\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}}}\right) \bar{\sigma}_i + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}}}\right) \bar{\sigma}_i^2\right)^{-1} > 0$ for all assets and σ_δ denotes the cross-agent variance of ESG preferences.

Equation (8) shows that, aggregating across agents, more information is acquired for both green and brown assets, as the cross-agent average signal precision increases with the departure from green neutrality. This is a consequence of the marginal benefit of information acquisition being quadratic in ESG preferences, implying that the additional information acquired by funds with ESG preferences compatible with the asset's sustainability profile outweighs the reduced information precision in funds with preferences not aligned with the asset's ESG attributes. In contrast, sustainability-neutral assets do not trigger additional information gains.

As the aggregate signal precision varies with ESG characteristics, the model suggests implications for the asset's price informativeness. Price informativeness, defined

perceived nonpecuniary component of the risk factor payoff, $\left(\delta_j - \bar{\delta}_i\right) g_i$, does not offset the positive risk-based expected payoff component, $\rho\bar{\sigma}_i$. The assumption reflects the intuition that nonpecuniary motives contribute only for a fraction of the perceived total payoff. The calibration exercise in Online Appendix B supports this assumption, showing that the relation between ESG preferences and signal precision is monotonic for an ample range of ESG scores and preferences.

as $\frac{\mathrm{Cov}[f_i,p_i]}{\mathrm{Std}[p_i]}$, refers to the asset price ability to predict the future random payoff, which increases with the asset's signal precision, as demonstrated in Online Appendix A.4. Hence, price informativeness improves for assets with more extreme sustainability profiles and for which mutual fund investors display more heterogeneous ESG preferences.

In summary, the incorporation of ESG factors into investment decisions can enhance the recognition of the value of sustainable assets and expand the pool of investment opportunities. Both green and brown assets experience advantages from increased information acquisition, resulting in heightened price informativeness and, as addressed in the following, a larger active fund industry.

2.3 Stock holdings, tracking error, and performance

The preference of mutual funds for ESG investing has an impact on their (i) stock holdings, (ii) tracking error, and (iii) net payoff in excess of the market. First, we discuss the ESG-based tilt in the fund's optimal portfolio, with the proof presented in Online Appendix A.5.

Proposition 4. *The expected ESG-based deviation of the fund's optimal portfolio from the market can be measured by*

$$\mathrm{E}\left[q_{ij}-\bar{q}_i\right]=\frac{\Delta\delta_{ij}g_i}{\rho\bar{\sigma}_i}+\left(1+\frac{\Delta\delta_{ij}g_i}{\rho\bar{\sigma}_i}\right)\frac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}},\qquad i=1,\ldots,N-1 \tag{9}$$

$$\mathrm{E}\left[q_{Nj}-\bar{q}_N\right]=\frac{\Delta S_{Nj}}{\bar{\sigma}_N^{-1}}-\sum_{i=1}^{N-1}b_i\mathrm{E}\left[q_{ij}-\bar{q}_i\right], \tag{10}$$

where $\bar{q}_i=\int q_{ij}\mathrm{d}j$ is the market position in asset i, $\Delta\delta_{ij}=\delta_j-\bar{\delta}_i$, and $\Delta S_{ij}=S_{ij}-\bar{S}_i$. The expected ESG score of the portfolio is $\mathrm{E}\left[G_j\right]=\sum_{i=1}^{N-1}\mathrm{E}\left[q_{ij}-\bar{q}_i\right]g_i$.

Both ESG-perceptive and ESG-indifferent funds diversify their holdings across the sustainability spectrum, but due to their ESG motivations, ESG-perceptive funds overweight green assets in their portfolios relative to ESG-indifferent funds.[7] The

[7] While the model does not impose short sale constraints, expected portfolio tilts in Proposition 4 are referred to a (long-only) market benchmark. For realistic parameter values, the optimal portfolio

portfolio tilt is determined by two forces. The first operates even under symmetric information, reflecting the ratio of nonpecuniary ($\Delta\delta_{ij}g_i$) and risk-based ($\rho\bar{\sigma}_i$) components of perceived expected returns. This force grows in the difference between the fund's nonpecuniary motives and the average motives across agents, resulting in a positive tilt when the fund's ESG preferences align with the asset's ESG profile, and negative otherwise. It applies to all assets except for the aggregate asset, which is assumed to be neutral in terms of sustainability. The second effect considers the tendency of agents to overweight assets with more precise signals than the average, with this contribution becoming more significant when nonpecuniary motives are higher than average, and reduced otherwise.[8] Compared to the benchmark of symmetric information, the positive interaction between information acquisition and ESG motives implies even larger portfolio tilts towards green (brown) assets for funds that are more (less) ESG perceptive than the average. In summary, the expected ESG profile of the optimal portfolio is essentially greener for funds that are more ESG perceptive, with this effect amplified by increasing signal precision.

Our derivations shed light on the implications of optimal information and portfolio policies, which raises an important question: do optimal policies of funds with different ESG preferences differ significantly? To answer this, we calculate the expected utility loss that an ESG-perceptive fund would experience if it adopted the optimal information and portfolio decisions of an ESG-indifferent fund. While Geczy et al. (2021) evaluated utility losses associated with socially responsible investing, we derive the utility loss based on our proposed equilibrium, which differs from their optimization experiments. Notably, past work has reported utility losses based on symmetric information, where the value function is assessed at the deterministic op-

is then mostly characterized by long positions, as we also verify through calibration. Indeed, funds can be positively exposed to assets with incompatible ESG profiles for diversification. This also aligns with common practice, as ESG-perceptive funds are more likely to collect information about green assets and take long positions, instead of specializing in brown assets and taking short positions, due to the significant financial loss in shorting brown assets. Similarly, ESG-indifferent funds tend to specialize in brown assets rather than bearing the costs of short selling green assets.

[8]While Van Nieuwerburgh and Veldkamp (2009) document information and portfolio choices tilted towards assets for which agents are initially endowed with a higher signal precision, in our framework, information choices arise endogenously from the interaction between the agent's ESG preferences and the asset's ESG profiles. As informational advantages occur when ESG preferences deviate from the average, heterogeneous preferences are required for the effect to manifest.

timal and suboptimal portfolio strategies. The utility loss reflects the discrepancy between the evaluated utility measures.

When information acquisition is present, the value function is influenced by the precision of multiple signals and the stochastic strategy that depends on the realization of signals. We provide the technical details in the Online Appendix A.6. We use calibration experiments to assess the utility loss and confirm that the expected loss, which is solely due preference for sustainable investing, can be significant, accounting for as high as 21.5% of the expected net payoff.

Given the potential significance of ESG-based tilts, we examine their impact on the dispersion of stock positions, tracking error, and fund performance. Portfolio dispersion is defined as the sum of the squared distances of individual equity positions relative to the market portfolio: $\mathrm{Disp}_j = \mathrm{E}\left[\sum_{i=1}^{N-1}(q_{ij}-\bar{q}_i)^2\right]$. The dispersion in portfolio positions induces a tracking error for the optimal portfolio relative to the market. Tracking error is defined as the variance of the difference between the portfolio and market returns: $\mathrm{TE}_j = \mathrm{Var}\left[\sum_{i=1}^{N}(q_{ij}-\bar{q}_i)(f_i-p_i)\right]$. The proposition below, derived in Online Appendix A.7, states the determinants of portfolio dispersion and tracking error.

Proposition 5. *The dispersion of portfolio positions across individual assets ($i = 1,\dots,N-1$) is given by*

$$\mathrm{Disp}_j = \sum_{i=1}^{N-1}\left(\frac{S_{ij}}{\rho^2}+\frac{V_{ii}\Delta S_{ij}^2}{\rho^2}+\left(\frac{\Delta\delta_{ij}g_i}{\rho\bar{\sigma}_i}+\left(1+\frac{\Delta\delta_{ij}g_i}{\rho\bar{\sigma}_i}\right)\frac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}}\right)^2\right), \tag{11}$$

where $V_{ii} = \bar{\sigma}_i\left(1+\left(\rho^2\sigma_{\mathcal{X}}+\bar{S}_i\right)\bar{\sigma}_i\right)$ is the unconditional variance of the net payoff of risk factor i. The tracking error of the optimal portfolio is given by

$$\mathrm{TE}_j = \sum_{i=1}^{N}\left(\left(\bar{\sigma}_i^2+\frac{V_{ii}}{\rho^2}\right)S_{ij}+2\left(\frac{V_{ii}}{\rho}\Delta S_{ij}\right)^2+\left(\frac{\Delta\delta_{ij}g_i}{\rho\bar{\sigma}_i}+\left(2+\frac{\Delta\delta_{ij}g_i}{\rho\bar{\sigma}_i}\right)\frac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}}\right)^2 V_{ii}\right). \tag{12}$$

Portfolio dispersion and tracking error consist of three components. The first is associated with signal realization and is present even when agents have identical ESG preferences and signal precision. This is because a random signal realized in period

1, even if drawn from the same distribution, affects the optimal portfolio in period 2. The second component is driven by the squared difference between an agent's signal precision and the average market-wide precision. If an agent observes signals that are either more or less precise than the average signal, the optimal portfolio will deviate more substantially from the market portfolio. The third component reflects the interaction between the monetary and nonpecuniary components. As previously demonstrated, this interaction could result in mutual funds overweighting stocks that align with their preferred sustainability profiles, with more pronounced tilts for higher levels of information acquisition.

To gain more insight into how ESG preferences can impact dispersion and tracking error, we consider a simplified setting where assets have identical posterior variances ($\bar{\sigma}_i = \bar{\sigma}$) and aggregate ESG preferences ($\bar{\delta}_i = \bar{\delta}$). As shown in Online Appendix A.8, the sensitivity of the fund signal precision, defined as the cross-asset average of the signal precision, $\hat{S}_j = \frac{1}{N}\sum_{i=1}^{N} S_{ij}$, to the departure of its ESG preference from the aggregate, $\left|\delta_j - \bar{\delta}\right|$, is given by

$$\frac{\partial \hat{S}_j}{\partial \left|\delta_j - \bar{\delta}\right|} = \frac{\sigma_g}{2\rho\kappa} \left|\delta_j - \bar{\delta}\right| , \tag{13}$$

where σ_g stands for the cross-asset variance of ESG scores. This equation shows that the departure of the fund ESG preference from the aggregate determines the sensitivity of the signal precision to the preference for holding green stocks. As the preference of an above-average ESG-perceptive investor rises, the average signal precision improves. Likewise, for a below-average ESG investor, as the preference for ESG investing diminishes, the average signal precision also improves. The effect, resulting from the quadratic relation between the asset's ESG profile and the marginal benefit of information acquisition displayed in Equation (7), is stronger for higher dispersion of the assets' ESG profiles (σ_g) and lower information cost (κ).

Proposition 5 thus suggests that portfolio dispersion and tracking error increase when the assets held by the funds deviate from green neutrality and when the fund's ESG preference departs from the aggregate. The effect is amplified by information acquisition, i.e., when the fund is more active.

To evaluate the fund's performance, we compute the fund payoff in excess of the market using a method similar to Kacperczyk et al. (2016). The expected excess net payoff is defined as $\mathrm{EENP}_j = \mathrm{E}\left[\sum_{i=1}^{N}(q_{ij} - \bar{q}_i)(f_i - p_i)\right]$. The proposition below provides the details with derivation in Online Appendix A.9.

Proposition 6. *The expected net payoff in excess of the market is given by*

$$\mathrm{EENP}_j = \sum_{i=1}^{N} \underbrace{\left(\frac{\Delta\delta_{ij} g_i}{\rho\bar{\sigma}_i} + \left(1 + \frac{\Delta\delta_{ij} g_i}{\rho\bar{\sigma}_i}\right)\frac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}}\right)}_{\mathrm{E}\left[\mathcal{Q}_{ij} - \bar{\mathcal{Q}}_i\right]} \underbrace{\left(\rho\bar{\sigma}_i - \bar{\delta}_i g_i\right)}_{\mathrm{E}\left[\mathcal{F}_i - \mathcal{P}_i\right]} + \sum_{i=1}^{N} \underbrace{\frac{V_{ii}}{\rho}\Delta S_{ij}}_{\mathrm{Cov}\left[\mathcal{Q}_{ij} - \bar{\mathcal{Q}}_i, \mathcal{F}_i - \mathcal{P}_i\right]}. \tag{14}$$

The first component of performance is the sum of the risk factor expected net payoffs, $\mathrm{E}\left[\mathcal{F}_i - \mathcal{P}_i\right]$, multiplied by the corresponding unconditional portfolio tilts, $\mathrm{E}\left[\mathcal{Q}_{ij} - \bar{\mathcal{Q}}_i\right]$. This component would be negative for ESG-perceptive funds and positive for ESG-indifferent ones since the former funds overweight green assets, characterized by a lower equilibrium expected net payoff. The second component reflects the skill in stock picking implied by private signals. A more precise conditioning signal leads to a higher covariance between the portfolio tilt and the risk factor net payoff. This component is proportional to the sum of the signal precisions in excess of the average, i.e., ΔS_{ij}, multiplied by the risk factor net payoff variances, i.e., V_{ii}. A fund that is more informed than the average on a specific asset generates a positive contribution to the expected payoff, while a less informed fund generates a negative contribution.

In the presence of managerial skills, an active ESG-perceptive fund can either underperform or outperform the market, depending on the strength of its skills. This means that the incremental positive expected return resulting from managerial skills, captured by the second term in fund performance, can partially or fully offset the return reduction attributable to holding green assets. Furthermore, if we control for the amount of information acquired, i.e., fixing ΔS_{ij} across agents and assets, ESG-indifferent funds are expected to deliver higher returns than ESG-perceptive funds.

To provide more insight into how ESG motives interact with active fund performance, we examine a simplified economy consisting of two groups of funds: ESG-perceptive and ESG-indifferent, each with the same size and ESG preferences of

$\delta_P > 0$ and $\delta_I = 0$, respectively. The funds can invest in two assets: a green asset with a score of $\bar{g} > 0$ and a brown asset with a score of $-\bar{g}$, where both assets have identical posterior variances, i.e., $\bar{\sigma}_{gr} = \bar{\sigma}_{br} = \bar{\sigma}$. ESG-perceptive funds receive a signal with precision $\bar{S} + \Delta S$ for the green asset, and with precision $\bar{S} - \Delta S$ for the brown asset. ESG-indifferent funds receive signals with precisions $S - \Delta S$ and $\bar{S} + \Delta S$ for the green and the brown assets, respectively. The signal precisions reflect the inference from Proposition 2 that ESG-perceptive (ESG-indifferent) funds acquire more information about green (brown) asset payoffs. Then, the expected net payoffs in excess of the market are given by

$$\text{EENP}_P = -\frac{\delta_P^2 \bar{g}^2}{2\rho\bar{\sigma}}, \tag{15}$$

$$\text{EENP}_I = \frac{\delta_P^2 \bar{g}^2}{2\rho\bar{\sigma}} + 2\delta_P \bar{g} \frac{\Delta S}{\bar{\sigma}^{-1}}. \tag{16}$$

In the simplified economy, the expected excess net payoff of an ESG-perceptive fund is not affected by the fund's signal precision for the following rationale. Although an ESG-perceptive fund with additional signal precision will invest more in the lower expected return green asset, managerial skills can leverage the informational advantage of the conditioning private signal to fully offset the negative effect of investing in such an asset. On the other hand, a brown fund benefits from having higher signal precision on the brown asset because it results in both a higher unconditional exposure to an asset delivering higher financial payoffs and an incremental performance attributable to the conditioning signal.

Equations (15) and (16) illustrate that information acquisition has an asymmetric impact on the performance of equally skilled ESG-perceptive and ESG-indifferent funds. Therefore, when analyzing the performance of active funds with heterogeneous ESG motives, controlling for an ESG benchmark that prices passive investments would only partially explain their alpha. Specifically, in the presence of an ESG factor, the performance gap between ESG-perceptive and ESG-indifferent funds would still be $-2\delta_P \bar{g} \frac{\Delta S}{\bar{\sigma}^{-1}}$.

While empirically testing the difference in expected net payoff between green and brown funds is challenging, our calibration experiments, detailed in Online Appendix

B, offer additional insights into its quantitative implications. The empirical challenge stems from two primary reasons. First, fund skills remain unobserved. Second, during the sample period, green assets yielded returns higher than anticipated. The discrepancy between realized and expected returns has been analyzed by Pástor et al. (2022) and Avramov et al. (2024). It is important to note that this section concentrates on the expected net payoff in excess of the market, while our calibration experiments suggest that the key findings are also applicable to the CAPM alpha.

2.4 The cross-section of asset payoffs

We are now prepared to derive and interpret the cross-section of the expected net stock payoffs. Utilizing the price equations outlined in Proposition 1, we can express the cross-section of expected net payoffs as follows.

Proposition 7. *The expected net payoffs for the aggregate and individual assets are*

$$\mathrm{E}\left[f_N - p_N\right] = \rho \bar{\sigma}_N, \tag{17}$$

$$\mathrm{E}\left[f_i - p_i\right] = b_i \mathrm{E}\left[f_N - p_N\right] + \rho \bar{\sigma}_i - \bar{\delta}_i g_i. \tag{18}$$

The expected net payoff for the aggregate asset can be expressed as the product of the risk aversion and the posterior variance of the payoff. For individual stocks, financial intermediaries' preferences for holding green assets affect the expected net payoffs in two ways. First, information acquisition decisions directly impact the expected net payoff through the posterior variance $\bar{\sigma}_i$, which is reduced to a greater extent for higher values of green or brown. This implies that the relation between ESG profile and expected net payoff is concave. Second, information decisions tilt the negative linear relation between ESG score and expected return that characterizes symmetric information. In particular, ESG preferences $\bar{\delta}_i$ are specific to each asset and equal to the precision-weighted average of agents' preferences for sustainable investing. As ESG-perceptive agents acquire more information about green assets, the asset color and ESG preferences are positively correlated, which increases the concavity of the ESG-expected net payoff relation.

Thus, the expected net payoff for green assets is lower due to two forces. The first is associated with the nonpecuniary benefits from holding green investments. The second originates from the lower posterior variance of the payoff of a greener asset, attributable to a more precise signal, and from the higher asset-specific ESG preferences. Hence, the negative relation between the expected net payoff and the ESG rating deepens for green assets.

For brown assets, the forces work in opposite directions. On the one hand, as the asset becomes browner, its expected payoff becomes higher due to the nonpecuniary channel. On the other hand, the signal precision is higher and the asset-specific ESG preferences are lower, both triggering a reduced expected payoff. An unreported calibration experiment suggests that, for reasonable parameter values, the nonpecuniary channel dominates. Hence, by integrating through the forces, brown assets earn higher returns on average, but the negative association between the ESG profile and the expected net payoff is weakened.

Equation (18) proposes an asset pricing model that is based on intermediaries and viewed through the lens of an information acquisition setting. He and Krishnamurthy (2018) suggest that intermediary-based asset pricing relies on the presence of an intermediary sector and a household sector. Some households do not directly invest in intermediated assets and instead delegate their investments to the intermediary sector. Frictions create a wedge between the household and intermediary valuations of assets, leading to the involvement of intermediaries in equilibrium.

In our setting, mutual funds can be viewed as a group of individuals who collaborate to share the cost of information acquisition. Investing in complex assets requires costly information acquisition, making it challenging for individuals to access such assets. Forming a fund allows individuals to share the information cost, enabling them to actively participate in trading risky assets. Therefore, in our setting, households implicitly delegate the active funds to trade on their behalf.

2.5 Scope of the active fund management industry

The rise in equilibrium aggregate signal precision for both green and brown assets, as displayed in Equation (3), implies that economic agents are motivated to invest more effort in developing comprehensive investment strategies. Consequently, there is an expansion in the overall scope of active management driven by a preference for sustainable investing. Previous studies, such as Pástor and Stambaugh (2012) and Pástor et al. (2015), have already explored the scope of the active fund industry. Our research demonstrates that sustainable investing can have a positive effect on the overall scope of the active asset management industry, leading to a greater amount of information being purchased in equilibrium.

To quantify the additional information due to ESG motives, in Online Appendix A.10 we show that the component in the market-wide average (across agents and assets) signal precision, $\hat{\bar{S}} = \frac{1}{N}\sum_{i=1}^{N}\left(\int_j S_{ij}\mathrm{d}j\right)$, explicitly associated with ESG considerations is given by:

$$\hat{\bar{S}}_{ESG} = \frac{\sigma_\delta \sigma_g}{4\kappa\rho}. \tag{19}$$

The equation above suggests that ESG motives contribute to the overall size of the active fund industry, as they lead mutual funds to purchasing incremental information in equilibrium. ESG-induced information acquisition only applies in the presence of cross-asset dispersion in ESG attributes (σ_g) and cross-fund dispersion in ESG preferences (σ_δ). The incremental information positively interacts with managerial skills. In particular, when the fund managers are more skilled (lower κ), the ESG-induced signal precision improves. Online Appendix B.2 offers a quantitative assessment of the increased level of information acquisition and the expanding scope of active fund management associated with sustainable investing. Notably, according to our calibration, the market-wide aggregate information cost increases by 4% due to ESG motives.

3 Data

3.1 Data sources

The sample of mutual funds consists of all U.S. actively managed equity mutual funds. Quarterly institutional equity holdings are acquired from the Thomson-Reuters mutual fund holdings database. The database contains quarter-end security holding information for all registered mutual funds that are required to report their holdings to the U.S. Securities and Exchange Commission (SEC). We match the holdings database with the Center for Research in Security Prices (CRSP) mutual fund database, which reports monthly net-of-fee returns and total net assets (TNAs), as well as other quarterly fund characteristics, such as the turnover and the expense ratio. We consolidate multiple share classes into portfolios by adding together share-class TNAs and by value weighting share-class characteristics (e.g., returns, fees) based on lagged share-class TNAs.

Equity funds are identified based on the objective codes from the CRSP following Kacperczyk et al. (2008). In our main analyses, we exclude funds identified by the CRSP "index_fund_flag" as index funds as well as funds whose name contains the following strings: "INDEX", "IDX", "IX", "INDX", "NASDAQ", "DOW", "MKT", "DJ", "S&P", "500", "BARRA", "WILSHIRE", and "RUSSELL". The sample is further restricted to funds that have TNA of at least $15 million to avoid the survivorship bias problem (see, e.g., Elton et al., 1996; Pástor et al., 2015), and we exclude observations prior to the fund's starting date reported by CRSP to prevent incubation bias (Evans, 2010). The mutual fund benchmark is defined based on the Primary Prospectus Benchmark from the Morningstar mutual fund database.

The stock sample consists of all NYSE/AMEX/Nasdaq common stocks with share codes 10 or 11; daily and monthly stock data are obtained from the CRSP database. We collect monthly ESG rating data from MSCI ESG Ratings, because MSCI is the world's largest provider of ESG ratings, covers more firms than other ESG raters, and provides the least noisy ESG scores (e.g., Eccles and Stroehle, 2020; Pástor et al., 2022). Quarterly and annual financial statement data come from the COMPUSTAT database. Analyst forecast data are provided by the Institutional Brokers' Estimate System (I/B/E/S).

The full sample spans the period from 2007 through 2021 due to the availability of MSCI ESG Ratings. The final sample contains 4,031 unique equity funds and 3,422 unique stocks. On average, there are 1,777 funds and 1,374 stocks per month.

3.2 Main variables

To measure the firm-level ESG rating, we start with the MSCI "Final Industry-Adjusted Company Score" ($INDUSTRY\_ADJUSTED\_SCORE$), which ranges from

0 to 10. Then, in each month, we sort all stocks according to the MSCI ESG score and calculate the percentile rank (normalized between -0.5 and 0.5) for each stock, labeled *Stock ESG*. The departure of firm ESG profile from green neutrality is computed as the absolute value of *Stock ESG*, labeled *Stock ESGDev*.

Next, we measure the ESG preferences of mutual funds. While ESG-perceptive funds naturally hold greener assets, the portfolio-level ESG rating (value weighted based on holdings) may not be an ideal proxy for the fund ESG preferences because mutual funds make investment decisions based on ESG and non-ESG characteristics (e.g., value investing), and ESG and non-ESG characteristics could be correlated. Therefore, it is critical to control for non-ESG characteristics and separate ESG preferences from other investment styles.[9] To proceed, we consider a comprehensive list of 94 firm characteristics,[10] including those commonly used in portfolio construction due to their return predictability and/or related to firms' ESG profile, such as size, book-to-market, profitability, investment, past performance, and tangibility.[11] Since the MSCI ESG scores are industry-adjusted, we rank all 94 non-ESG characteristics within each industry-month and normalize these ranks between 0 and 1. We do not perform such industry adjustment for dummy variables (e.g., sin stock indicator). The ranks for missing characteristics are set to be 0.5 (industry median).

We adopt the least absolute shrinkage and selection operator (LASSO) regression to accommodate a large number of regressors. In each month, we regress the MSCI ESG scores on the 94 industry-adjusted and normalized stock characteristics and obtain the estimated residuals, labeled *Stock Residual ESG*.[12] *Stock Residual ESG*

[9] We do not use an off-the-shelf proxy such as Morningstar sustainability rating because it only covers a short sample period from 2018 and is designed to evaluate the relative ESG risks of the underlying holdings within portfolios. We aim to identify fund ESG preferences that observable firm characteristics cannot explain.

[10] Details on each of the 94 firm characteristics can be found in the Appendix in Green et al. (2017) and Internet Appendix Table A.6 in Gu et al. (2020). We thank Jeremiah Green for making the SAS code used by Green et al. (2017) available via his website, https://sites.google.com/site/jeremiahrgreenacctg/home. To avoid forward-looking biases, monthly characteristics are delayed by at most one month, and quarterly and annual characteristics are delayed by at least four months and six months, respectively.

[11] For instance, Liang and Renneboog (2017) document that large, profitable firms invest more in corporate social responsibility, and Hsu et al. (2023) show that a firm's toxic emission intensity decreases with its size and increases with asset tangibility.

[12] The influential stock characteristics in the LASSO regression include size, illiquidity, idiosyn-

measures a firm's ESG profile that is orthogonal to other firm characteristics. Finally, we define the fund-level ESG preference as the investment value-weighted average of *Stock Residual ESG* in a fund's most recently reported holding portfolio (normalized between 0 and 1), labeled *Fund ESG Preference*. To measure how the fund ESG preference departs from the aggregate, we subtract 0.5 (market-level ESG preference) from *Fund ESG Preference* and then take the absolute value, labeled *Fund ESGDev*.

To capture the heterogeneous ESG preferences among mutual funds in stock investment, the dispersion in ESG preferences for a stock, labeled *Stock ESGDisp*, is defined as the standard deviation of *Fund ESG Preference* across all funds holding that stock. The standard deviation is investment value-weighted to account for the relative importance of individual fund's ESG preference.[13] Online Appendix Table A.1 provides a detailed definition for each variable.

3.3 Summary statistics

We report the summary statistics in Table 1. Panel A reports the means, medians, standard deviations, and quantile distributions of the monthly stock ESG ratings, the dispersion in ESG preferences for a stock, and other stock characteristics. Panel B reports similar statistics for the fund characteristics. The average stock ESG rating (*Stock ESG*) is 0.004 with a standard deviation of 0.290.[14] Notably, the average dispersion in ESG preferences for a stock (*Stock ESGDisp*) is 0.189 with a standard deviation of 0.039, indicating that mutual funds display dispersed preferences in ESG investing.[15] This further motivates us to investigate the role of heterogeneous ESG preferences across funds, in addition to firm ESG attributes and fund ESG preferences.

cratic return volatility, bid-ask spread, and current ratio, and all of them have more than 5% inclusion probability on average over the entire sample period.

[13]Unreported analyses using equal-weighted standard deviation also confirm our findings.

[14]While we normalize the ESG ratings to be between −0.5 and 0.5 for the entire universe of covered firms, the summary statistics only include stocks used in later analyses that require additional data regarding other firm characteristics. Therefore, the average ESG rating is approximately zero (although not exactly zero), and the distribution of the stock ESG ratings may slightly deviate from a uniform distribution.

[15]To put this in perspective, for a stock equally held by two funds with ESG preferences at the 35^{th} and 65^{th} percentile, respectively, the dispersion in ESG preferences is 0.212.

4 Price informativeness

We first examine the implications of sustainable investing for the asset price informativeness. As shown in Proposition 3, the aggregate signal precision improves when a firm's ESG profile departs from green neutrality and its investors display more dispersed ESG preferences. As prices become more informative upon higher aggregate signal precision (Online Appendix A.4), the model predicts higher price informativeness in the presence of (i) a departure from green neutrality and (ii) heterogeneous ESG preferences.

We follow the empirical work of Bai et al. (2016) and, consistent with our model, measure price informativeness as the ability of the current asset price to predict the future payoff. To test the model predictions, we estimate the following annual Fama and MacBeth (1973) regression:

$$\begin{aligned}\frac{E_{i,y+h}}{A_{i,y}} = \alpha + \beta_1 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) + \beta_2 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDev_{i,y} + \beta_3 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDisp_{i,y} \\ + \beta_4 ESGDev_{i,y} + \beta_5 ESGDisp_{i,y} + \beta_6 \left(\frac{E_{i,y}}{A_{i,y}}\right) + cN_{i,y} + \varepsilon_{i,y+h}, \qquad (20)\end{aligned}$$

where $E_{i,y+h}$ is the earnings before interest and taxes of stock i in year $y+h$, $A_{i,y}$ is the total assets, $M_{i,y}$ is the market capitalization, $ESGDev_{i,y}$ is the departure of firm ESG profile from green neutrality, and $ESGDisp_{i,y}$ is the stock-level heterogeneity in fund ESG preferences. Vector N stacks all other stock-level control variables: the *IO*, *Log(Asset)*, *Leverage*, *Tangibility*, *Log(Sales)*, *Cash*, *Log(Analyst Coverage)*, and *Analyst Dispersion*.

The β_1 coefficient measures the extent to which the current stock market valuation predicts future earnings and proxies for the price informativeness at the market level (Bai et al., 2016). The β_2 and β_3 coefficients capture the incremental effect of departure from green neutrality and heterogeneous ESG preferences, respectively, allowing us to test the model prediction in the cross-section. This empirical specification and the choice of control variables closely follow Kacperczyk et al. (2021). Online Appendix Table A.1 provides a detailed definition for each variable. We also report Newey and West (1987) adjusted t-statistics.

We tabulate the results in Table 2. We focus on the one-year ($h = 1$, Models 1–4), three-year ($h = 3$, Models 5–8), and five-year ($h = 5$, Models 9–12) forecasting horizons. Consistent with the model prediction, the β_2 and β_3 coefficients are positive and statistically significant in all specifications, suggesting that stocks with extreme ESG profiles and those held by investors with more heterogeneous ESG preferences display high price informativeness. As shown in Model 2 (Model 3), a one-standard-deviation increase in *Stock ESGDev* (*Stock ESGDisp*) is associated with 41.3% (28.4%) higher price informativeness in the next year.[16] The results are similar for the joint specification (Model 4) and robust for longer horizons (Models 5–12). Finally, our findings remain intact using alternative price informativeness measures based on cash flows from operations and free cash flows (results reported in Online Appendix Table A.2).

Our findings suggest that sustainable investing not only provides capital to green firms so they can generate greater social impact but also has broader implications for the financial market. To optimize the asset allocation with ESG considerations, active funds make information acquisition decisions according to their ESG preferences, firm ESG profiles, and the heterogeneity in ESG preferences across all market participants. The informed trading from active funds further improves the price efficiency of the stocks in their desired investment universe.

5 Mutual fund investment

5.1 Stock holdings

The information acquisition decision translates into mutual fund portfolio choices. The model obviously predicts that ESG-perceptive (ESG-indifferent) funds overweight green (brown) stocks. However, the degree of overweighting rises with the total signal precision (Proposition 4). In the presence of low signal precision, both ESG-perceptive and ESG-indifferent funds demand less risky assets in their preferred

[16]The increase in price informativeness is computed as $(0.041 \times 0.144) / (0.004 + 0.041 \times 0.251) = 41.3\%$, where 0.004 and 0.041 are the regression coefficients of *Log(M/A)* and *Log(M/A)×Stock ESGDev* in Model 2, and 0.251 and 0.144 are the sample mean and standard deviation of *Stock ESGDev* (Table 1 Panel A).

investment universe; hence, they are less affected by ESG considerations. Therefore, signal precision should also amplify the positive relationship between the stock ESG rating and the ownership gap, i.e., the difference in portfolio positions between ESG-perceptive and ESG-indifferent funds. We proceed with the empirical test.

For each stock, we compute the percentage fund ownership based on their ESG preferences. We identify ESG-perceptive (ESG-indifferent) funds, i.e., green (brown) funds, as those with a fund ESG preference in the top (bottom) quintile across all funds at the end of each month.[17] We then estimate the following monthly Fama and MacBeth (1973) regression:

$$IO_{i,t} = \alpha + \beta_1 ESG_{i,t-1} + \beta_2 ESG_{i,t-1} \times Char_{i,t-1} + \beta_3 Char_{i,t-1} + cN_{i,t-1} + \varepsilon_{i,t}, \quad (21)$$

where $IO_{i,t}$ refers to a list of mutual fund ownership measures of stock i in month t: green fund ownership, brown fund ownership, and the difference in ownership between green and brown funds. $ESG_{i,t-1}$ is the stock ESG rating, and $Char_{i,t-1}$ refers to a list of stock characteristics that proxy for the information uncertainty, information acquisition activities, and the subsequent signal precision: *IVOL* is the idiosyncratic volatility; *RETVOL* is the total return volatility; *Active IO* is the active mutual fund ownership; and *Log(Analyst Coverage)* is the logarithm of the number of analysts following a firm.[18] Specifically, idiosyncratic volatility and total return volatility capture the uncertainty in investment payoff, and institutional investors and sell-side analysts are among the most influential information producers in financial markets (e.g., Boehmer and Kelley, 2009; Kelly and Ljungqvist, 2012). Vector N stacks all other stock-level control variables: the *Log(Size)*, *Log(BM)*, *ROE*, *I/A*, *1M*

[17] In the empirical section, we label funds with high ESG perceptiveness as green funds and those with low ESG perceptiveness as brown funds for notational convenience. *Green IO* and *Brown IO* refer to the percentage ownership from funds with high and low ESG perceptiveness, respectively. Note that we measure fund ESG preferences through *Stock Residual ESG*, which is orthogonal to other firm characteristics that affect fund investment. Therefore, green (brown) funds should not be confused with funds that merely hold greener (browner) assets based on portfolio-level ESG ratings.

[18] In the model, agents can purchase costly signals regarding the random risk factor payoffs as formulated in Equation (2). While the signal precision is not directly observed, it is inversely related to information uncertainty and positively related to information acquisition activities; therefore, we consider various related proxies in the empirical analyses.

Return, and *12M Return*. Online Appendix Table A.1 provides a detailed definition for each variable. We also report Newey and West (1987) adjusted t-statistics.

Table 3 presents the results, with Panel A for green fund ownership and Panel B for brown fund ownership, respectively. Several findings are worth noting. First, as expected, the stock ESG rating is positively (negatively) associated with green (brown) fund ownership, confirming the model prediction that ESG-perceptive (ESG-indifferent) funds overweight green (brown) stocks after controlling for other non-ESG characteristics (Models 1–2).

Next, ESG-perceptive (ESG-indifferent) funds invest less in green (brown) stocks in the presence of high idiosyncratic volatility and total return volatility (Models 3–4), but invest more in green (brown) stocks with high active mutual fund ownership and analyst coverage (Models 5–6). Our findings support the model prediction that signal precision amplifies the effect of ESG considerations on mutual fund portfolio choices. For instance, a one-standard-deviation increase in *IVOL* (*RETVOL*) is associated with 25.4% (30.4%) lower ESG-induced ownership from green funds and 31.5% (37.2%) lower ESG-induced ownership from brown funds.[19] In addition, a one-standard-deviation increase in *Active IO* (*Log(Analyst Coverage)*) is associated with 41.0% (27.6%) higher ESG-induced ownership from green funds and 81.1% (50.0%) higher ESG-induced ownership from brown funds.

Panel C of Table 3 further examines the difference in ownership between *Green IO* and *Brown IO*. While the ownership gap increases with stock ESG ratings, the positive ESG-ownership gap relation attenuates when signal precision is low. The results hold for both standalone models (Models 3–6) and joint specifications (Models 7–8). For instance, a one-standard-deviation increase in *IVOL* (*RETVOL*) is associated with 28.4% (33.8%) lower ESG-ownership gap sensitivity and a one-standard-deviation increase in *Active IO* (*Log(Analyst Coverage)*) is associated with 63.6% (38.5%) higher ESG-ownership gap sensitivity.

Our findings are also robust to controlling for a comprehensive set of stock characteristics. Consistent with the prior literature (e.g., Liang and Renneboog, 2017;

[19] The impact of *IVOL* on ESG-induced ownership from green funds (i.e., ESG-Green IO sensitivity) is computed as $(-0.240 \times 1.188) / (1.494 - 0.240 \times 1.549) = -25.4\%$, where 1.494 and -0.240 are the regression coefficients of *Stock ESG* and *Stock ESG*$\times$*IVOL* in Panel A Model 3, and 1.549 and 1.188 are the sample mean and standard deviation of *IVOL* (Table 1 Panel A).

Dyck et al., 2019; Hsu et al., 2023), large, growth firms tend to have better ESG performance and thus attract more ESG-perceptive funds. In addition, ESG-perceptive funds are more likely to hold stocks with low profitability and past returns, possibly due to their nonpecuniary motives. As expected, ESG-indifferent funds often specialize in stocks with opposite attributes.

Overall, our findings reinforce the notion that both signal precision and ESG considerations matter for mutual fund portfolio choices. Consistent with the model prediction, imprecise signals lower investor demand for risky assets, especially in their preferred investment universe. Therefore, mutual fund investment is less affected by ESG considerations when signal precision is low. In the presence of unprecedented growth in sustainable investing, our findings highlight the interplay between ESG preferences and information acquisition in shaping the investment practices of active fund management.

5.2 Portfolio dispersion and tracking error

While the previous analysis focuses on mutual fund ownership in individual stocks, we move on to analyzing fund overall portfolio choices. As shown in Equations (7) and (13), in the presence of heterogeneous ESG preferences across funds, active funds acquire more firm-specific information when the fund ESG preference departs from the aggregate. This intuition, along with Proposition 5, leads to a testable hypothesis: the portfolio dispersion and tracking error increase when funds display more extreme ESG preferences, and the effect is amplified by information acquisition. To test this hypothesis, we further exploit the heterogeneity in information acquisition by considering active funds vs. index funds, and expect more ESG-induced portfolio dispersion and tracking error among actively managed mutual funds. We estimate the following monthly Fama and MacBeth (1973) regression:

$$\begin{aligned} DISP_{j,t} = \alpha &+ \beta_1 Fund\,ESGDev_{j,t-1} + \beta_2 Active_{j,t-1} \\ &+ \beta_3 Fund\,ESGDev_{j,t-1} \times Active_{j,t-1} + cM_{j,t-1} + \varepsilon_{j,t}, \end{aligned} \tag{22}$$

where $DISP_{j,t}$ refers to a list of fund characteristics that proxy for the portfolio dispersion and tracking error of fund j in month t: *HHI* measures the deviation of the fund's investment strategy from its benchmark portfolio; and *TE* measures the deviation of fund returns from its benchmark portfolio returns.[20] $Fund\,ESGDev_{j,t-1}$ is the departure of fund ESG preference from the aggregate, and $Active_{j,t-1}$ is a dummy variable that equals 1 for an active fund and 0 otherwise. Vector M stacks all other fund-level control variables: the *Fund Return*, *Fund Flow*, *Log(Fund TNA)*, *Expense Ratio*, *Fund Turnover*, *Log(Fund Age)*, and *Flow Volatility*. We expect to see a positive value of β_3, as the model predicts. Online Appendix Table A.1 provides a detailed definition for each variable. We also report Newey and West (1987) adjusted t-statistics.

We tabulate the results in Table 4. Consistent with the model prediction, the departure of fund ESG preference from the aggregate is positively associated with portfolio dispersion and tracking error. Importantly, the impact of *Fund ESGDev* on portfolio dispersion and tracking error is more prominent among active funds, as indicated by a significant *Fund ESGDev*×*Active* coefficient. For instance, a one-standard-deviation increase in *Fund ESGDev* is associated with 55.7% higher portfolio dispersion among active funds (Model 3) (scaled by the sample mean of the corresponding dispersion measure).[21] This represents an 83.3% increase compared to index funds. Similarly, a one-standard-deviation increase in *Fund ESGDev* is associated with 18.7% higher tracking error among active funds (Model 6) (scaled by the sample mean of the corresponding dispersion measure), while the effect for index funds is insignificant.

Overall, our findings support the model prediction that when mutual fund ESG preferences depart from the aggregate, they are more likely to adopt distinct trading strategies and deviate from a passive benchmark, possibly due to their enhanced information acquisition activities. The fund-level results also corroborate the evidence on stock-level price informativeness (Table 2), i.e., the information acquisition decisions and portfolio choices of active funds further improve the price efficiency of the

[20] Note that Proposition 5 formulates the portfolio dispersion and tracking error using the market portfolio as a benchmark. In the empirical analyses, we employ a fund-specific benchmark from its prospectus to better capture the active deviations in mutual fund investment.

[21] The impact of portfolio dispersion is computed as $(0.114+0.095)\times 0.144/0.054 = 55.7\%$, where 0.114 and 0.095 are the regression coefficients of *Fund ESGDev* and *Fund ESGDev*×*Active* in Model 3, respectively, 0.144 is the standard deviation of *Fund ESGDev* (Table 1 Panel B), and 0.054 is the sample mean of *HHI* (Table 1 Panel B).

stocks in their desired investment universe.

6 Asset pricing implications

Having shown that ESG considerations affect mutual fund stock holdings, portfolio and return dispersions through their information acquisition decisions, we now investigate how sustainable investing affects stock returns in the cross-section. As shown in Proposition 7, the model predicts that the expected return (i) diminishes with the stock ESG rating and mutual funds' ESG preferences and (ii) increases with the posterior variance (inversely related to the signal precision). In addition, ESG-perceptive funds (i.e., green funds) acquire more information about green stocks, and ESG-indifferent funds (i.e., brown funds) acquire more information about brown stocks, as formulated in Equation (7). On the one hand, high green fund ownership implies more information acquisition and lower variance for green stocks, leading to lower expected returns for green stocks and amplifying the negative ESG-expected return relation. On the other hand, high brown fund ownership also indicates more information acquisition and lower variance for brown stocks, leading to lower expected returns for brown stocks and weakening the negative ESG-expected return relation. While we expect a negative linear relation between ESG rating and expected return under symmetric information, the ESG-expected return relation is concave in the presence of information acquisition. Additionally, we expect the negative ESG-expected return relation to be more pronounced among green stocks with high green fund ownership and brown stocks with low brown fund ownership, i.e., when information acquisition and the corresponding posterior variance, fund ESG preference, and stock ESG rating affect asset prices in the same direction.

One caveat is that while equilibrium asset pricing predicts a negative relation between the ESG rating and *expected* return due to the nonpecuniary benefits of holding green stocks, we only observe ex post *realized* returns. Furthermore, Pástor et al. (2022) document that U.S. green stocks outperformed brown stocks during the last decade, due to an unexpected shift in investors' tastes for green holdings. To ensure that the wedge between expected and realized returns does not distort our findings, we consider the implied cost of capital (ICC) as a proxy for the expected return. We follow the regression-based approach proposed by Hou et al. (2012) and the adjustment by Pástor et al. (2022) to forecast earnings and compute the ICC. Notably, for each stock-month, the ICC is the discount rate that equates the stock's market value to the present value of its expected future cash flows.[22] In comparing alternative measures, either based on cross-sectional regressions or analysts' earnings forecasts, Lee et al. (2021) find that the adopted approach produces the most precise cross-sectional expected return estimates, even compared to composite measures averaging multiple ICC estimates. As a robustness check, we collect ESG ratings from additional data vendors, which allows us to examine a longer sample period and test the model prediction using *realized* returns in early years (Online Appendix C.1).

The analysis proceeds as follows. At the end of month t, stocks are first sorted into terciles according to their green fund ownership (*Green IO*). Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 15 (3×5) portfolios.[23] The low- (high)-green-fund-ownership portfolios comprise the bottom (top) tercile of stocks based on the green fund ownership, and the low- (high)-ESG-rating portfolios comprise the bottom (top) quintile of stocks based on the ESG rating. For each of the 15 portfolios, we compute the value-weighted ICC in month $t+1$ and rebalance the portfolios at the end of month $t+1$. Within each tercile of portfolios sorted by green fund ownership, we also compute the high (top quintile of ESG rating) minus low (bottom quintile of ESG rating) portfolio ICC ("HML-R"), indicating the expected return predictability of ESG ratings after controlling for information acquisition. We then report the time-series averages of the monthly ICCs for each of the 15 portfolios and the long-short strategy. Similarly, within each quintile of portfolios sorted by stock ESG ratings, we compute the high

[22]To obtain the future cash flows, we forecast earnings from the cross-sectional regressions for the first three years ahead. In addition, we assume that the expected return on equity (ROE) mean-reverts to the industry median ROE by the end of year 12 and forecast ROE from year 4 to year 12 using a linear interpolation. The residual income from year 12 onward is regarded as a perpetuity. Details on the ICC estimation can be found in Hou et al. (2012) and the Internet Appendix in Pástor et al. (2022). While the ICC estimated from this approach measures the annualized expected return, we divide it by 12 to obtain monthly ICC. Later, we construct monthly-rebalanced portfolios with a one-month holding period.

[23]We employ a conditional sort to better understand how information acquisition tilts the ESG-expected return relation, while unreported results show that an independent sort yields similar findings.

(top tercile of green fund ownership) minus low (bottom tercile of green fund ownership) portfolio ICC ("HML-G"). Finally, we consider a univariate portfolio sort based on ESG ratings (green fund ownership) and report similar statistics in the column (row) titled "All".

In addition to the raw portfolio ICCs, we report the risk-adjusted ICCs from (i) the CAPM, i.e., only adjusting for the market factor (MKT, defined as the excess return on the value-weighted CRSP market index over the one-month Treasury bill rate); (ii) the Fama-French six-factor model (FF6), consisting of the market factor (MKT), the size factor (SMB, defined as small minus big firm return premium), the book-to-market factor (HML, defined as the high book-to-market minus the low book-to-market return premium), the profitability factor (RMW, defined as the robust minus weak return premium), the investment factor (CMA, defined as the conservative minus aggressive return premium), and the momentum factor (MOM) (Fama and French, 2018);[24] and the characteristic-adjusted ICCs from (iii) the Daniel et al. (1997) model (DGTW), that is, the stock ICCs are adjusted by the style average, where stock styles are created by triple-sorting stocks into 125 ($5\times5\times5$) size, book-to-market, and momentum portfolios. The standard errors in all estimations are corrected for autocorrelation using the Newey and West (1987) method.

Table 5 reports the results, with Panel A1 for raw ICC and CAPM-adjusted ICC and Panel B1 for FF6-adjusted ICC and DGTW-adjusted ICC.[25] Several findings are worth noting. First, green stocks (i.e., stocks in the top ESG rating quintile) exhibit lower ICC (DGTW-adjusted ICC) than brown stocks (i.e., stocks in the bottom ESG rating quintile), and the monthly difference in a univariate sort is 0.135% (0.084%). The negative ESG-ICC relation is in line with the nonpecuniary benefits of ESG investing and supports our model setup. Consistent with Pástor et al. (2022), our findings suggest that, compared with the realized return, ICC is a better proxy for the expected return.

Second, consistent with the model prediction, the ESG-ICC relation is concave,

[24]We thank Kenneth French for making the common factor returns available via his website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[25]Note that the results using CAPM- and FF6-adjusted ICCs are qualitatively and quantitatively similar to ICC; therefore, we focus on ICC and DGTW-adjusted ICC when discussing the findings.

as demonstrated in Figure 1.[26] Specifically, the ESG-ICC relation is more negative among greener stocks and less negative among browner stocks. For instance, the difference in ICC (DGTW-adjusted ICC) between stocks in the bottom and third ESG quintiles is 0.029% (0.012%), while a similar difference between stocks in the third and top ESG quintiles rises sharply to 0.106% (0.072%). All differences are significant at the 1% level.

Third, the negative ESG-ICC relation is more pronounced among stocks with high green fund ownership. When green fund ownership is low, green stocks display an insignificant 0.021% (0.020%, only significant at the 10% level) lower ICC (DGTW-adjusted ICC) per month than brown stocks. When green fund ownership is high, green stocks display a significant 0.115% (0.066%) lower ICC (DGTW-adjusted ICC) per month than brown stocks. The monthly difference in ICC (DGTW-adjusted ICC) spread between high- and low-green-fund-ownership portfolios is significant at −0.094% (−0.046%). This confirms the model prediction that information acquisition makes stock investment less risky (i.e., implied by a lower posterior variance), lowering the expected returns.

In Panels A2 and B2 of Table 5, we report similar statistics by replacing green fund ownership with brown fund ownership (*Brown IO*). As expected, the negative ESG-ICC relation is also stronger among stocks with low brown fund ownership. When brown fund ownership is low, green stocks display 0.138% (0.079%) lower ICC (DGTW-adjusted ICC) per month than brown stocks. When brown fund ownership is high, the ICCs for green stocks and brown stocks are no longer significantly different. The monthly difference in ICC (DGTW-adjusted ICC) spread between high- and low-brown-fund-ownership portfolios is significant at 0.134% (0.077%).

We provide a battery of additional analyses to assess the robustness of our results. First, we employ the composite ICC measure in Lee et al. (2021), which takes the equal-weighted average of four commonly used ICC variants: the discounted residual income model-based ICC proposed by Gebhardt et al. (2001) and Claus and Thomas (2001) and the abnormal earnings model-based ICCs proposed by Easton (2004) and Ohlson and Juettner-Nauroth (2005). Lee et al. (2021) use the mechanical earnings

[26]Unreported results confirm the concave ESG-ICC relation in decile portfolios sorted by stock ESG ratings.

forecasts from the cross-sectional forecast model of Hou et al. (2012) as inputs.[27] We tabulate the results in Online Appendix Table A.3 and our main findings remain robust to the composite ICC measure. We continue to find a concave ESG-ICC relation, as demonstrated in Online Appendix Figure A.3. The negative ESG-ICC relation is also more pronounced among stocks with high green fund ownership and low brown fund ownership.

In all previous analyses, we identify green/brown funds based on *Fund ESG Preference* after controlling for non-ESG characteristics. As a robustness check, we rely on portfolio ESG scores (i.e., the investment value-weighted average of stock ESG ratings in a fund's holding portfolio), and green (brown) funds are those holding greener (browner) assets. In the interest of brevity, we tabulate the results in Online Appendix Table A.4 and our main findings remain intact using alternative green/brown fund ownership measures.

Collectively, consistent with the model prediction, we show that active investors' ESG preferences play a vital role in the cross-section of stock prices beyond the ESG profile of the firm, through their information acquisition decisions. The negative ESG-ICC relation is more pronounced stocks with high green fund ownership and low brown fund ownership because information acquisition lowers the perceived riskiness of the stock, which enhances the low expected return for green stocks but offsets the high expected return for brown stocks. Therefore, our findings document a novel beneficial effect of sustainable investing: green firms can enjoy a lower cost of capital due to (i) the nonpecuniary benefits of holding green stocks as proposed in prior literature and (ii) lower risk due to enhanced information acquisition. This allows them to make more socially responsible investments and generate higher social impact.

We also assess the cross-sectional prediction using *realized* returns, and report the results in Online Appendix C.1. We primarily focus on the period January 2001–October 2012, characterized by stable preferences for sustainable investments. To obtain ESG ratings also in early years, we construct a consensus measure averaging

[27]We thank the authors for making the firm-level expected return proxies available via the website: https://leesowang2021.github.io/data/. Since our main ICC measure builds on the framework of Gebhardt et al. (2001) but uses regression-based earnings forecasts, we consider the composite of the mechanical-based ICCs as a natural extension.

ratings provided by three different data vendors, i.e., MSCI ESG Ratings, MSCI KLD, and Sustainalytics. As displayed in Online Appendix Table A.5, the negative ESG-return relation only holds among stocks with high green fund ownership. For instance, the high-Green-IO, high-ESG stocks generate a significant CAPM alpha of -0.304% per month and underperform the high-Green-IO, low-ESG stocks by 0.588% per month (Panel A1). Furthermore, we confirm a significantly negative ESG-return relation among stocks with low brown fund ownership. Indeed, the low-Brown-IO, low-ESG stocks generate a significant CAPM alpha of 0.455% per month and outperform low-Brown-IO, high-ESG stocks by 0.579% per month (Panel A3). After 2012, the average realized returns do not align with the predictions due to unexpected shifts in ESG preferences, while the ICC measure used in the baseline analysis remains unaffected by such shocks (Online Appendix Table A.6).

Overall, our empirical results build a compelling case suggesting that sustainable investing plays a prominent role in determining the information acquisition decisions and investment strategies of active mutual funds, the cross-section of asset prices, and the price informativeness of the underlying assets. As more institutions seek sustainable investing, we will likely observe an even more substantial impact in the future.

7 Conclusion

We analyze the equilibrium implications of fund managers making information acquisition decisions based on financial and social objectives. The model produces a rich set of predictions regarding fund managers' information decisions and portfolio choices, the scope of the active fund industry, and the cross-section of asset prices and price informativeness.

In equilibrium, ESG-perceptive (ESG-indifferent) funds are incentivized to acquire a greater amount of information about green (brown) assets and less information about brown (green) assets. However, the overall information acquisition increases due to ESG motives, thereby amplifying active management. The additional information characterizes any individual asset that deviates from green neutrality. As more information is purchased, the asset price becomes more informative about future profitability. Moreover, the portfolio tilts of mutual funds are more pronounced for assets with higher signal precision. These portfolio tilts are associated with increasing fund's tracking error and dispersion in stock holdings.

Information acquisition amplifies the negative ESG-expected return relation for green assets. Specifically, the expected return for green assets is lower due to (i) the preference for holding sustainable investments and (ii) the lower posterior variance of the green asset payoff due to higher signal precision. In contrast, the two forces act in opposite directions for brown assets. Taken together, in the presence of information acquisition, the ESG-expected return relation becomes concave.

Empirical tests offer corroborative evidence for the proposed model. First, stocks with greater departure from green neutrality and held by funds with more heterogeneous ESG preferences display higher price informativeness. Second, while ESG-perceptive (ESG-indifferent) funds invest more in green (brown) stocks, both types of funds invest less in their preferred investment universe as the uncertainty and opaqueness of the investable assets rises. Third, mutual funds are more likely to adopt distinct trading strategies and deviate from a passive benchmark when their ESG preferences depart from the aggregate, and this effect is amplified by information acquisition. Fourth, the negative ESG-expected return relation is concave, being more pronounced among stocks held by more ESG-perceptive funds and less ESG-indifferent funds. Indeed, information acquisition implies even lower expected returns for green stocks, while it partially offsets the high expected returns for brown stocks. The model predictions are further quantified in the calibration exercise.

Our findings highlight that ESG considerations play an essential role in shaping mutual funds' information acquisition decisions, their portfolio choices, and the size of the active fund industry. As a result, sustainable investing not only provides capital to green firms, but also improves the overall efficiency of the financial market due to ESG-induced information acquisition. Information acquisition further reduces the risk of sustainable investing and tilts the negative ESG-expected return relation, lowering the cost of capital of green firms so that they can generate greater social impact. Our proposed information acquisition framework could also help explain the mixed empirical evidence documented in prior studies.

The paper suggests avenues for future research. First, due to the lack of consistency in the ESG ratings provided by different rating agencies, it could be helpful to account for the rating uncertainty and the additional information acquired about assets' ESG profiles. Second, it could be useful to explicitly account for delegation, i.e., (uninformed) households delegate their investments to the (informed) intermediary sector. Then, testable equilibrium restrictions on fund flows and ESG motives can be derived. Third, De Angelis et al. (2023) and Avramov et al. (2024) highlight the asset pricing implications of dynamic preferences for sustainability and ESG profiles under symmetric information. These effects could be studied in the presence of informational asymmetries. Finally, while the ESG profile of an asset is exogenous in our setting, activist shareholders can engage in corporate ESG activities and improve the sustainability performance of targeted firms. We leave these and other extensions for future work.

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Table 1: Summary Statistics

This table presents the summary statistics for the data used in the paper during the period from 2007 to 2021. Panels A and B report the means, standard deviations, medians, and quantile distributions of stock and fund characteristics, respectively. Online Appendix Table A.1 provides a detailed definition for each variable.

	Mean	Std.Dev.	Quantile Distribution				
			10%	25%	Median	75%	90%
Panel A: Stock Characteristics							
Stock ESG	0.004	0.290	-0.398	-0.234	0.005	0.257	0.405
Stock ESGDev	0.251	0.144	0.050	0.131	0.245	0.377	0.452
Stock ESGDisp	0.189	0.039	0.141	0.159	0.186	0.215	0.241
E/A	0.030	0.192	-0.121	0.016	0.060	0.111	0.173
Log(M/A)	-0.093	1.114	-1.745	-0.731	0.005	0.663	1.262
IO	0.726	0.247	0.341	0.592	0.796	0.919	0.998
Log(Asset)	7.346	1.890	4.918	5.996	7.316	8.596	9.863
Leverage	0.573	0.268	0.217	0.377	0.568	0.762	0.899
Tangibility	0.491	0.185	0.245	0.370	0.494	0.594	0.730
Log(Sales)	6.657	2.126	4.208	5.433	6.748	8.037	9.233
Cash	0.140	0.167	0.009	0.025	0.081	0.189	0.352
Log(Analyst Coverage)	2.216	0.797	1.099	1.792	2.303	2.833	3.178
Analyst Dispersion	0.126	0.404	0.007	0.014	0.030	0.080	0.230
Green IO	1.467	2.203	0.000	0.017	0.438	2.121	4.454
Brown IO	3.666	4.084	0.166	0.758	2.319	5.230	8.948
IVOL	1.549	1.188	0.615	0.831	1.215	1.857	2.816
RETVOL	2.242	1.594	0.971	1.291	1.812	2.641	3.918
Active IO	17.904	9.152	6.373	11.502	17.325	23.582	29.777
Log(Size)	8.072	1.541	6.160	6.904	7.971	9.127	10.216
Log(BM)	-1.009	0.884	-2.107	-1.472	-0.895	-0.405	-0.045
ROE	0.020	0.153	-0.051	0.006	0.026	0.048	0.085
I/A	0.136	0.385	-0.078	-0.006	0.057	0.157	0.366
1M Return	1.156	11.460	-11.066	-4.615	1.055	6.537	13.088
12M Return	0.148	0.477	-0.311	-0.100	0.101	0.315	0.598
Panel B: Fund Characteristics							
Fund ESGDev	0.247	0.144	0.049	0.122	0.246	0.371	0.447
HHI	0.054	0.151	0.000	0.008	0.017	0.034	0.084
TE	0.134	0.359	0.001	0.019	0.048	0.116	0.280
Fund Return	0.776	4.765	-4.798	-1.414	1.031	3.355	5.941
Fund Flow	-0.109	5.230	-3.195	-1.465	-0.484	0.614	2.928
Log(Fund TNA)	6.128	1.799	3.716	4.726	6.110	7.391	8.537
Expense Ratio	1.030	0.408	0.500	0.800	1.027	1.266	1.530
Fund Turnover	0.708	0.793	0.120	0.250	0.490	0.860	1.430
Log(Fund Age)	4.973	0.771	3.936	4.564	5.093	5.464	5.790
Flow Volatility	4.611	11.268	0.481	0.869	1.757	3.812	8.462

Table 2: Stock Price Informativeness

This table presents the results of the following annual Fama-MacBeth regression and their corresponding Newey-West adjusted t-statistics:

$$\frac{E_{i,y+h}}{A_{i,y}} = \alpha + \beta_1 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) + \beta_2 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDev_{i,y} + \beta_3 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDisp_{i,y}$$
$$+ \beta_4 ESGDev_{i,y} + \beta_5 ESGDisp_{i,y} + \beta_6\left(\frac{E_{i,y}}{A_{i,y}}\right) + cN_{i,y} + \varepsilon_{i,y+h},$$

where $E_{i,y+h}$ is the earnings before interest and taxes of stock i in year y+h, $A_{i,y}$ is the total assets, $M_{i,y}$ is the market capitalization, $ESGDev_{i,y}$ is the departure from green neutrality, and $ESGDisp_{i,y}$ is the stock-level heterogeneity in the fund ESG preferences. Vector N stacks all other stock-level control variables, namely, the IO, Log(Asset), Leverage, Tangibility, Log(Sales), Cash, Log(Analyst Coverage), and Analyst Dispersion. Models 1-4, Models 5-8, and Models 9-12 report the results when h = 1, h = 3, and h = 5, respectively. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Dep. Var. =	$E_{i,y+1}/A_{i,y}$				$E_{i,y+3}/A_{i,y}$				$E_{i,y+5}/A_{i,y}$			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Log(M/A)	0.011**	0.004	-0.005	-0.008	0.012*	0.002	-0.018	-0.020	0.011	-0.007	-0.029*	-0.038*
	(2.77)	(0.72)	(-0.88)	(-1.19)	(2.11)	(0.27)	(-1.26)	(-1.30)	(1.16)	(-0.47)	(-1.93)	(-1.93)
Log(M/A) × Stock ESGDev		0.041***		0.031***		0.062***		0.041**		0.113**		0.085*
		(6.03)		(3.80)		(3.31)		(2.33)		(3.05)		(2.01)
Log(M/A) × Stock ESGDisp			0.097***	0.083***			0.174**	0.148**			0.235***	0.202***
			(6.93)	(7.23)			(2.70)	(2.60)			(5.31)	(5.59)
Stock ESGDev		0.006		0.005		0.007		0.003		-0.006		-0.011
		(0.95)		(0.67)		(0.72)		(0.23)		(-0.35)		(-0.56)
Stock ESGDisp			-0.024	-0.023			0.079***	0.077***			0.037	0.033
			(-0.93)	(-0.90)			(3.28)	(3.17)			(1.32)	(1.18)
E/A	0.827***	0.818***	0.816***	0.810***	0.845***	0.832***	0.830***	0.823***	0.921***	0.902***	0.898***	0.887***
	(40.71)	(41.87)	(40.56)	(41.52)	(13.89)	(13.65)	(13.27)	(13.12)	(13.94)	(14.05)	(13.89)	(13.88)
IO	0.010**	0.009**	0.011**	0.010**	0.009	0.008	0.011	0.010	0.000	0.003	0.003	0.004
	(2.29)	(2.35)	(2.73)	(2.69)	(1.16)	(1.14)	(1.46)	(1.34)	(0.00)	(0.17)	(0.14)	(0.24)
Log(Asset)	-0.007***	-0.007***	-0.007***	-0.007***	-0.017**	-0.017**	-0.018***	-0.018***	-0.017***	-0.018***	-0.018***	-0.019***
	(-3.40)	(-3.19)	(-3.55)	(-3.23)	(-2.94)	(-3.01)	(-3.36)	(-3.35)	(-6.05)	(-5.66)	(-6.59)	(-6.13)
Leverage	0.036***	0.035***	0.034***	0.034***	0.031**	0.029**	0.027*	0.027*	0.028	0.024	0.022	0.019
	(4.69)	(4.72)	(4.50)	(4.60)	(2.27)	(2.19)	(2.10)	(2.07)	(1.56)	(1.25)	(1.20)	(0.99)
Tangibility	-0.015*	-0.016**	-0.017**	-0.018**	-0.044**	-0.046**	-0.046***	-0.047***	-0.026	-0.031*	-0.029*	-0.033*
	(-1.87)	(-2.16)	(-2.19)	(-2.42)	(-2.85)	(-2.95)	(-3.19)	(-3.23)	(-1.71)	(-1.95)	(-1.85)	(-2.06)
Log(Sales)	0.012***	0.013***	0.013***	0.013***	0.022***	0.022***	0.023***	0.023***	0.018***	0.020***	0.020***	0.022***
	(4.34)	(4.53)	(4.63)	(4.76)	(4.07)	(4.32)	(4.65)	(4.82)	(5.05)	(5.65)	(5.44)	(6.05)
Cash	-0.061***	-0.055***	-0.056***	-0.052***	-0.052*	-0.044*	-0.044*	-0.039	-0.057**	-0.042**	-0.048**	-0.038*
	(-5.06)	(-5.12)	(-4.96)	(-5.08)	(-1.97)	(-1.80)	(-1.81)	(-1.72)	(-2.65)	(-2.29)	(-2.21)	(-2.01)
Log(Analyst Coverage)	-0.007***	-0.007***	-0.008***	-0.007***	-0.007	-0.007*	-0.008*	-0.008*	0.003	0.003	0.002	0.002
	(-4.21)	(-4.12)	(-4.56)	(-4.43)	(-1.69)	(-1.78)	(-2.06)	(-2.11)	(0.49)	(0.45)	(0.29)	(0.26)
Analyst Dispersion	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	0.005	0.006	0.004	0.005
	(-0.71)	(-0.66)	(-0.84)	(-0.80)	(-0.61)	(-0.53)	(-0.58)	(-0.51)	(1.51)	(1.71)	(1.30)	(1.47)
Constant	-0.013*	-0.015**	-0.011*	-0.013**	0.020	0.014	0.008	0.004	0.042*	0.032	0.035	0.027
	(-1.89)	(-2.53)	(-1.92)	(-2.17)	(1.25)	(0.87)	(0.56)	(0.28)	(2.01)	(1.50)	(1.54)	(1.21)
Obs	32,136	32,136	32,136	32,136	24,691	24,691	24,691	24,691	18,602	18,602	18,602	18,602
R-squared	0.738	0.740	0.740	0.742	0.527	0.530	0.532	0.534	0.386	0.392	0.392	0.397

Table 3: Stock ESG Rating, Signal Precision, and Mutual Fund Ownership

Panel A presents the results of the following monthly Fama-MacBeth regression and their corresponding Newey-West adjusted t-statistics:

$$IO_{i,t} = \alpha + \beta_1 ESG_{i,t-1} + \beta_2 ESG_{i,t-1} \times Char_{i,t-1} + \beta_3 Char_{i,t-1} + cN_{i,t-1} + \varepsilon_{i,t},$$

where $IO_{i,t}$ is the green fund ownership of stock i in month t, $ESG_{i,t-1}$ is the ESG rating, and $Char_{i,t-1}$ refers to a list of stock characteristics: IVOL is the idiosyncratic volatility; RETVOL is the total return volatility; Active IO is the active mutual fund ownership, and Log(Analyst Coverage) is the logarithm of the number of analysts following a firm. Vector N stacks all other stock-level control variables, namely, the Log(Size), Log(BM), ROE, I/A, 1M Return, and 12M Return. Panels B and C report similar statistics when the dependent variables are the brown fund ownership and the difference in ownership between green and brown funds, respectively. We identify the green (brown) funds as those with a fund ESG preference in the top (bottom) quintile across all funds at the end of each month. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Green Fund Ownership Regressed on Lagged Stock ESG Rating and Signal Precision

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Stock ESG	1.092***	1.088***	1.494***	1.611***	0.216**	0.280	-0.332	-0.200
	(22.82)	(22.85)	(24.12)	(21.51)	(2.29)	(1.03)	(-1.19)	(-0.71)
Stock ESG × IVOL			-0.240***				-0.277***	
			(-6.21)				(-7.17)	
Stock ESG × RETVOL				-0.215***				-0.256***
				(-6.32)				(-7.69)
Stock ESG × Active IO					0.049***		0.043***	0.044***
					(8.74)		(7.34)	(7.41)
Stock ESG × Log(Analyst Coverage)						0.418***	0.491***	0.493***
						(3.97)	(5.17)	(5.26)
IVOL	0.019		0.023				0.008	
	(0.73)		(1.01)				(0.30)	
RETVOL		-0.004		0.012				-0.014
		(-0.14)		(0.51)				(-0.48)
Active IO	0.061***	0.061***			0.061***		0.063***	0.063***
	(11.45)	(11.37)			(11.44)		(12.03)	(11.98)
Log(Analyst Coverage)	0.017	0.020				0.213***	0.040	0.041
	(0.57)	(0.67)				(6.19)	(1.22)	(1.29)
Log(Size)	0.597***	0.591***	0.547***	0.543***	0.606***	0.468***	0.588***	0.582***
	(24.28)	(24.01)	(19.90)	(19.56)	(27.86)	(18.61)	(23.61)	(23.28)
Log(BM)	-0.250***	-0.247***	-0.322***	-0.319***	-0.255***	-0.315***	-0.249***	-0.246***
	(-9.56)	(-9.52)	(-11.33)	(-11.39)	(-9.50)	(-11.36)	(-9.71)	(-9.64)
ROE	-0.373***	-0.385***	-0.479***	-0.475***	-0.434***	-0.475***	-0.383***	-0.390***
	(-3.25)	(-3.40)	(-4.02)	(-4.07)	(-3.46)	(-3.70)	(-3.23)	(-3.30)
I/A	-0.153***	-0.154***	-0.063*	-0.065*	-0.150***	-0.069**	-0.148***	-0.149***
	(-4.64)	(-4.71)	(-1.79)	(-1.89)	(-4.27)	(-2.04)	(-4.43)	(-4.48)
1M Return	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.004***	-0.005***	-0.005***
	(-6.68)	(-6.27)	(-5.50)	(-5.20)	(-6.48)	(-4.75)	(-6.84)	(-6.52)
12M Return	-0.370***	-0.376***	-0.275***	-0.276***	-0.400***	-0.254***	-0.374***	-0.378***
	(-5.68)	(-5.67)	(-4.48)	(-4.46)	(-6.20)	(-3.87)	(-5.63)	(-5.63)
Constant	-4.680***	-4.600***	-3.193***	-3.149***	-4.703***	-3.011***	-4.720***	-4.629***
	(-20.53)	(-19.41)	(-12.63)	(-11.79)	(-22.98)	(-15.11)	(-19.44)	(-18.37)
Obs	246,946	246,947	247,307	247,308	246,947	247,308	246,946	246,947
R-squared	0.302	0.303	0.240	0.241	0.300	0.245	0.316	0.317

Panel B: Brown Fund Ownership Regressed on Lagged Stock ESG Rating and Signal Precision

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Stock ESG	-1.392***	-1.387***	-1.640***	-1.755***	0.828***	0.445	0.830***	0.820***
	(-26.62)	(-26.65)	(-21.42)	(-16.39)	(4.27)	(1.19)	(4.08)	(4.24)
Stock ESG × IVOL			0.308***				-0.001	
			(4.35)				(-0.02)	
Stock ESG × RETVOL				0.269***				0.008
				(4.45)				(0.17)
Stock ESG × Active IO					-0.125***		-0.125***	-0.126***
					(-11.24)		(-10.98)	(-11.10)
Stock ESG × Log(Analyst Coverage)						-0.717***	-0.013	-0.009
						(-4.85)	(-0.20)	(-0.14)
IVOL	-0.047		-0.103*				-0.037	
	(-1.20)		(-1.88)				(-0.97)	
RETVOL		-0.005		-0.030				0.004
		(-0.13)		(-0.60)				(0.11)
Active IO	0.180***	0.180***			0.178***		0.179***	0.179***
	(13.27)	(13.16)			(13.39)		(13.37)	(13.27)
Log(Analyst Coverage)	-0.171***	-0.179***				0.219***	-0.187***	-0.195***
	(-4.86)	(-5.04)				(8.33)	(-5.53)	(-5.71)
Log(Size)	-0.427***	-0.416***	-0.561***	-0.545***	-0.491***	-0.586***	-0.444***	-0.434***
	(-4.32)	(-4.29)	(-5.56)	(-5.51)	(-4.71)	(-6.46)	(-4.40)	(-4.38)
Log(BM)	0.530***	0.529***	0.385***	0.389***	0.548***	0.426***	0.527***	0.526***
	(8.16)	(8.09)	(5.81)	(5.76)	(8.24)	(6.20)	(8.21)	(8.12)
ROE	0.424**	0.447***	0.423**	0.475**	0.507***	0.650***	0.371**	0.398**
	(2.56)	(2.76)	(2.28)	(2.58)	(2.87)	(3.04)	(2.25)	(2.44)
I/A	0.007	0.004	0.187***	0.179***	-0.000	0.162**	-0.004	-0.009
	(0.13)	(0.08)	(2.83)	(2.70)	(-0.00)	(2.46)	(-0.08)	(-0.17)
1M Return	0.004***	0.004***	0.007***	0.007***	0.004***	0.006***	0.004***	0.004***
	(2.96)	(3.12)	(3.78)	(3.98)	(2.64)	(3.44)	(2.85)	(3.00)
12M Return	-0.012	-0.004	0.179*	0.199*	0.040	0.257**	0.001	0.010
	(-0.12)	(-0.04)	(1.68)	(1.93)	(0.37)	(2.49)	(0.01)	(0.10)
Constant	4.318***	4.171***	8.278***	8.064***	4.440***	7.861***	4.518***	4.377***
	(5.02)	(4.91)	(7.26)	(7.11)	(5.22)	(7.53)	(5.11)	(5.02)
Obs	246,946	246,947	247,307	247,308	246,947	247,308	246,946	246,947
R-squared	0.370	0.370	0.157	0.156	0.373	0.153	0.382	0.383

Table 3 (continued)

Panel C: Green–Brown Fund Ownership Gap Regressed on Lagged Stock ESG Rating and Signal Precision								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Stock ESG	2.484***	2.475***	3.134***	3.365***	-0.612***	-0.165	-1.162***	-1.020***
	(30.90)	(31.05)	(30.60)	(23.52)	(-2.64)	(-0.30)	(-2.95)	(-2.66)
Stock ESG × IVOL			-0.547***				-0.276***	
			(-6.54)				(-5.24)	
Stock ESG × RETVOL				-0.484***				-0.264***
				(-6.29)				(-5.43)
Stock ESG × Active IO					0.174***		0.168***	0.170***
					(14.43)		(14.48)	(14.85)
Stock ESG × Log(Analyst Coverage)						1.135***	0.504***	0.502***
						(5.38)	(4.32)	(4.30)
IVOL	0.066		0.126*				0.045	
	(1.05)		(1.79)				(0.72)	
RETVOL		0.001		0.042				-0.017
		(0.02)		(0.64)				(-0.28)
Active IO	-0.119***	-0.119***			-0.117***		-0.115***	-0.116***
	(-6.49)	(-6.45)			(-6.49)		(-6.41)	(-6.36)
Log(Analyst Coverage)	0.188***	0.199***				-0.006	0.227***	0.236***
	(3.54)	(3.75)				(-0.14)	(4.26)	(4.44)
Log(Size)	1.024***	1.007***	1.107***	1.088***	1.097***	1.053***	1.033***	1.016***
	(9.67)	(9.66)	(9.56)	(9.53)	(9.88)	(10.23)	(9.76)	(9.75)
Log(BM)	-0.779***	-0.777***	-0.707***	-0.708***	-0.804***	-0.741***	-0.775***	-0.772***
	(-9.65)	(-9.56)	(-8.92)	(-8.88)	(-9.63)	(-9.23)	(-9.74)	(-9.62)
ROE	-0.798***	-0.832***	-0.902***	-0.951***	-0.940***	-1.125***	-0.754***	-0.789***
	(-3.50)	(-3.71)	(-3.89)	(-4.15)	(-3.78)	(-4.37)	(-3.20)	(-3.38)
I/A	-0.160**	-0.159**	-0.250***	-0.244***	-0.150**	-0.231***	-0.144**	-0.140**
	(-2.41)	(-2.39)	(-3.32)	(-3.24)	(-2.16)	(-3.05)	(-2.13)	(-2.06)
1M Return	-0.010***	-0.010***	-0.012***	-0.012***	-0.010***	-0.010***	-0.010***	-0.010***
	(-5.25)	(-5.43)	(-5.36)	(-5.57)	(-4.79)	(-4.64)	(-5.21)	(-5.40)
12M Return	-0.358***	-0.372***	-0.454***	-0.475***	-0.440***	-0.511***	-0.374***	-0.388***
	(-2.61)	(-2.78)	(-3.17)	(-3.42)	(-3.02)	(-3.52)	(-2.64)	(-2.82)
Constant	-8.999***	-8.770***	-11.471***	-11.212***	-9.143***	-10.872***	-9.238***	-9.006***
	(-9.95)	(-9.68)	(-8.90)	(-8.69)	(-10.62)	(-9.40)	(-9.99)	(-9.73)
Obs	246,946	246,947	247,307	247,308	246,947	247,308	246,946	246,947
R-squared	0.338	0.339	0.268	0.268	0.340	0.264	0.353	0.354

Table 4: ESG-Induced Mutual Fund Portfolio Dispersion and Tracking Error

Models 1-3 present the results of the following monthly Fama-MacBeth regression and their corresponding Newey-West adjusted t-statistics:

$$DISP_{j,t} = \alpha + \beta_1 Fund\,ESGDev_{j,t-1} + \beta_2 Active_{j,t-1} + \beta_3 Fund\,ESGDev_{j,t-1} \times Active_{j,t-1} + cM_{j,t-1} + \varepsilon_{j,t},$$

where $DISP_{j,t}$ is the portfolio dispersion of fund j in month t computed with respect to the fund's benchmark (HHI), $Fund\,ESGDev_{j,t-1}$ is the departure of fund ESG preference from the aggregate, and $Active_{j,t-1}$ is a dummy variable that equals 1 for an active fund and 0 otherwise. Vector M stacks all other fund-level control variables, namely, the Fund Return, Fund Flow, Log(Fund TNA), Expense Ratio, Fund Turnover, Log(Fund Age), and Flow Volatility. Models 4-6 report similar statistics when the dependent variable is TE, defined as the tracking error computed with respect to the fund's benchmark. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Monthly Raw and CAPM-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings														
	ICC							CAPM-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.267***	0.220***	0.228***	0.253***	0.223***	-0.044	0.242***	0.210***	0.158***	0.167***	0.191***	0.167***	-0.043	0.183***
	(5.53)	(7.74)	(6.96)	(7.07)	(5.06)	(-1.15)	(7.02)	(3.66)	(4.05)	(4.05)	(4.20)	(3.19)	(-1.03)	(4.16)
Mid	0.152***	0.157***	0.199***	0.145***	0.090**	-0.061**	0.151***	0.085*	0.096**	0.132***	0.081**	0.037	-0.049*	0.088**
	(3.93)	(5.43)	(5.99)	(5.88)	(2.01)	(-2.10)	(5.40)	(1.84)	(2.32)	(3.23)	(2.40)	(0.71)	(-1.66)	(2.35)
High	0.022	-0.020	-0.027	-0.066**	-0.117***	-0.139***	-0.054*	-0.041	-0.078**	-0.091**	-0.126***	-0.180***	-0.140***	-0.116***
	(0.74)	(-0.59)	(-0.87)	(-2.11)	(-3.96)	(-8.07)	(-1.89)	(-1.12)	(-2.04)	(-2.43)	(-3.52)	(-5.01)	(-8.11)	(-3.32)
HML-G	-0.245***	-0.240***	-0.255***	-0.319***	-0.340***	-0.095**	-0.296***	-0.250***	-0.235***	-0.258***	-0.317***	-0.347***	-0.097**	-0.299***
	(-4.79)	(-8.27)	(-9.64)	(-9.55)	(-11.94)	(-2.13)	(-11.53)	(-4.82)	(-7.77)	(-9.89)	(-9.28)	(-11.97)	(-2.09)	(-11.44)
All	0.102***	0.086***	0.077**	0.025	-0.086***	-0.187***		0.041	0.026	0.016	-0.037	-0.147***	-0.188***	
	(2.92)	(2.78)	(2.19)	(0.76)	(-2.68)	(-10.50)		(0.95)	(0.62)	(0.38)	(-0.94)	(-3.82)	(-9.94)	
Panel A2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.062	0.049	0.031	-0.037	-0.111***	-0.173***	-0.032	-0.001	-0.014	-0.032	-0.095**	-0.175***	-0.174***	-0.094**
	(1.53)	(1.14)	(0.95)	(-0.95)	(-3.46)	(-7.32)	(-0.99)	(-0.03)	(-0.30)	(-0.86)	(-2.20)	(-4.46)	(-7.92)	(-2.47)
Mid	0.168***	0.111***	0.114***	0.059**	-0.010	-0.178***	0.092***	0.108**	0.054	0.053	-0.002	-0.070*	-0.178***	0.032
	(3.93)	(2.61)	(3.19)	(2.05)	(-0.34)	(-6.63)	(2.88)	(1.98)	(1.04)	(1.32)	(-0.06)	(-1.88)	(-6.28)	(0.77)
High	0.084***	0.128***	0.120***	0.107***	0.067***	-0.017	0.098***	0.025	0.066*	0.059	0.046	0.005	-0.020	0.037
	(3.09)	(4.99)	(4.81)	(4.42)	(2.89)	(-0.88)	(4.45)	(0.69)	(1.96)	(1.64)	(1.30)	(0.15)	(-1.06)	(1.13)
HML-B	0.023	0.079**	0.089***	0.144***	0.179***	0.156***	0.131***	0.026	0.080**	0.091**	0.141***	0.180***	0.154***	0.131***
	(0.50)	(2.10)	(2.66)	(4.59)	(6.79)	(4.47)	(4.96)	(0.62)	(2.05)	(2.57)	(4.46)	(6.55)	(4.70)	(4.84)
All	0.102***	0.086***	0.077**	0.025	-0.086***	-0.187***		0.041	0.026	0.016	-0.037	-0.147***	-0.188***	
	(2.92)	(2.78)	(2.19)	(0.76)	(-2.68)	(-10.50)		(0.95)	(0.62)	(0.38)	(-0.94)	(-3.82)	(-9.94)	
Panel B: Monthly FF6- and DGTW-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings														
	FF6-adjusted ICC							DGTW-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel B1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.199***	0.153***	0.161***	0.192***	0.163***	-0.036	0.176***	0.070**	0.030**	0.030**	0.049***	0.031*	-0.039	0.048***
	(3.66)	(4.12)	(4.16)	(4.51)	(3.40)	(-0.95)	(4.30)	(2.54)	(2.31)	(2.47)	(2.73)	(1.65)	(-1.43)	(3.75)
Mid	0.083**	0.092**	0.130***	0.081**	0.034	-0.049*	0.087***	0.034*	0.061***	0.094***	0.079***	-0.004	-0.038**	0.059***
	(2.17)	(2.40)	(3.32)	(2.55)	(0.78)	(-1.69)	(2.61)	(1.91)	(2.99)	(4.34)	(5.53)	(-0.27)	(-2.36)	(4.87)
High	-0.037	-0.081**	-0.092***	-0.129***	-0.178***	-0.141***	-0.115***	-0.012	-0.060***	-0.059***	-0.079***	-0.090***	-0.079***	-0.064***
	(-1.01)	(-2.37)	(-2.61)	(-3.79)	(-5.13)	(-8.16)	(-3.47)	(-0.73)	(-5.71)	(-5.92)	(-8.17)	(-10.64)	(-4.65)	(-9.92)
HML-G	-0.235***	-0.235***	-0.253***	-0.320***	-0.340***	-0.105**	-0.291***	-0.082**	-0.090***	-0.090***	-0.128***	-0.121***	-0.039	-0.112***
	(-4.66)	(-8.58)	(-10.23)	(-10.63)	(-12.54)	(-2.47)	(-12.05)	(-2.23)	(-5.14)	(-5.29)	(-5.86)	(-5.25)	(-1.16)	(-6.67)
All	0.041	0.022	0.015	-0.040	-0.145***	-0.186***		0.022*	0.005	0.009	-0.017**	-0.079***	-0.101***	
	(1.00)	(0.55)	(0.39)	(-1.09)	(-3.97)	(-11.10)		(1.76)	(0.43)	(0.81)	(-2.03)	(-13.21)	(-6.97)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.002	-0.013	-0.033	-0.097**	-0.171***	-0.173***	-0.093***	0.004	-0.024	-0.018	-0.056***	-0.090***	-0.094***	-0.050***
	(0.04)	(-0.30)	(-0.93)	(-2.44)	(-4.57)	(-7.75)	(-2.61)	(0.24)	(-1.30)	(-1.42)	(-4.05)	(-12.91)	(-5.06)	(-6.64)
Mid	0.108**	0.049	0.052	-0.006	-0.073**	-0.182***	0.030	0.070***	0.020	0.036**	0.005	-0.055***	-0.125***	0.019**
	(2.06)	(1.02)	(1.35)	(-0.15)	(-2.06)	(-6.72)	(0.75)	(3.19)	(1.20)	(2.05)	(0.50)	(-6.05)	(-5.51)	(2.24)
High	0.019	0.067**	0.052	0.039	0.004	-0.015	0.033	-0.018	0.005	0.003	-0.011	-0.037**	-0.019	-0.013
	(0.55)	(2.07)	(1.52)	(1.19)	(0.12)	(-0.82)	(1.07)	(-0.87)	(0.31)	(0.16)	(-0.81)	(-2.38)	(-0.94)	(-1.02)
HML-B	0.018	0.079**	0.084**	0.136***	0.175***	0.157***	0.126***	-0.022	0.029	0.021	0.045**	0.053***	0.076***	0.037**
	(0.42)	(2.34)	(2.50)	(4.71)	(6.64)	(4.74)	(4.99)	(-0.77)	(1.11)	(0.89)	(2.04)	(3.18)	(2.94)	(2.20)
All	0.041	0.022	0.015	-0.040	-0.145***	-0.186***		0.022*	0.005	0.009	-0.017**	-0.079***	-0.101***	
	(1.00)	(0.55)	(0.39)	(-1.09)	(-3.97)	(-11.10)		(1.76)	(0.43)	(0.81)	(-2.03)	(-13.21)	(-6.97)	

Table 5: Implied Cost of Capital of Portfolios Sorted by Mutual Fund Ownership and ESG Rating

In Panel A1, at the end of month t, stocks are first sorted into terciles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 15 (3×5) portfolios. The low- (high)-green-fund-ownership portfolios comprise the bottom (top) tercile of stocks based on the green fund ownership, and the low- (high)-ESG-rating portfolios comprise the bottom (top) quintile of stocks based on the ESG rating. For each of the 15 portfolios, we compute the value-weighted implied cost of capital (ICC) in month t+1 and rebalance the portfolios at the end of month t+1. We compute the ICC for each stock-month following Hou et al. (2012) and Pástor et al. (2022), and report the time-series averages of the monthly ICCs for each of the 15 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for portfolios sorted only by green fund ownership. The portfolio ICCs are further adjusted by the CAPM. Panel A2 reports similar statistics when we replace green fund ownership with brown fund ownership. We identify green (brown) funds as those with a fund ESG preference in the top (bottom) quintile across all funds at the end of each month. Panel B reports similar statistics based on Fama-French six-factor-adjusted ICCs (FF6) and characteristic-adjusted ICCs per Daniel et al. (1997) (DGTW). The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Monthly Raw and CAPM-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings

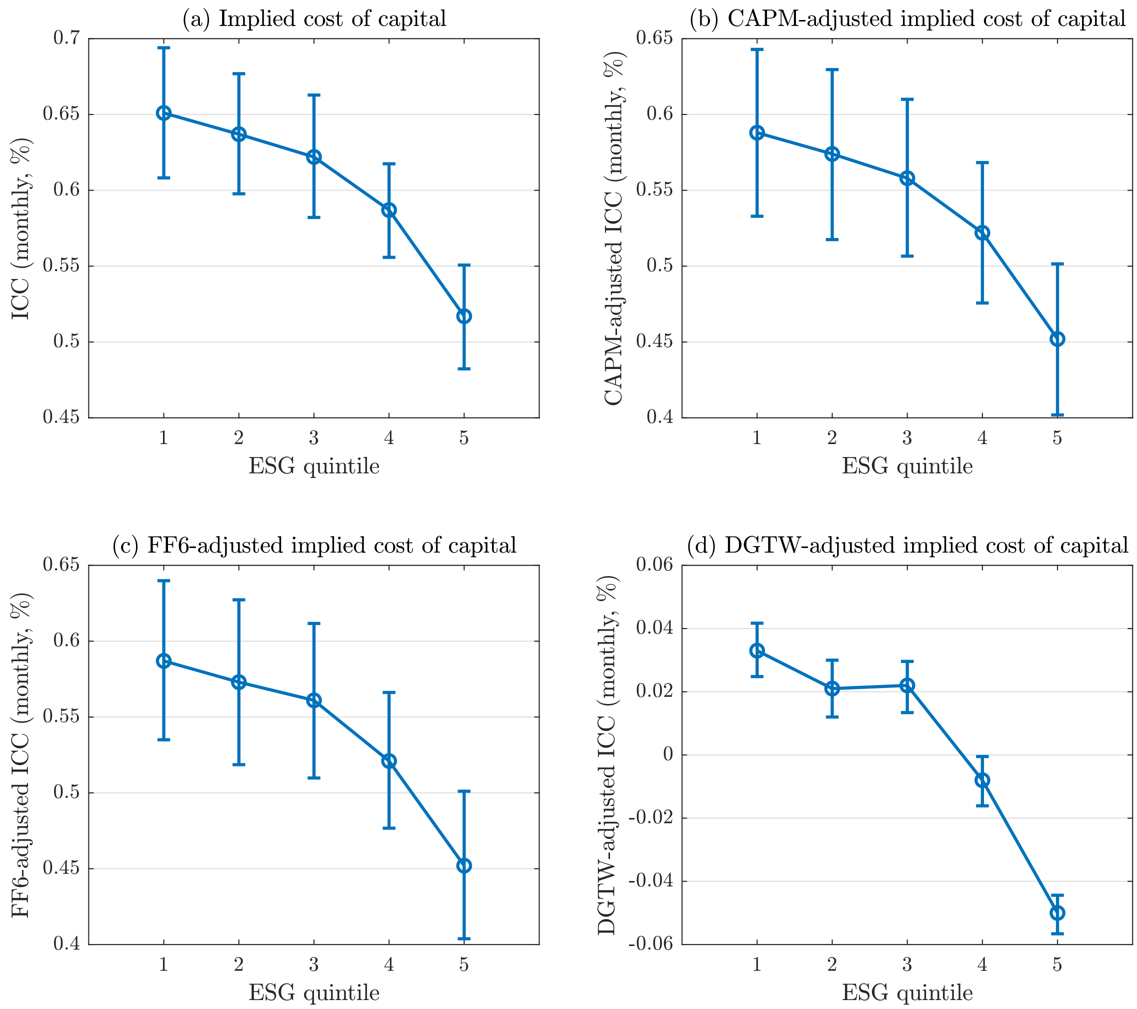
	ICC							CAPM-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.708***	0.676***	0.699***	0.666***	0.687***	-0.021	0.685***	0.644***	0.613***	0.637***	0.601***	0.625***	-0.019	0.623***
	(33.16)	(34.10)	(30.25)	(38.80)	(30.62)	(-1.55)	(35.15)	(21.41)	(22.60)	(21.64)	(24.31)	(22.53)	(-1.32)	(23.20)
2	0.686***	0.683***	0.682***	0.641***	0.590***	-0.096***	0.647***	0.622***	0.618***	0.619***	0.575***	0.528***	-0.095***	0.582***
	(31.27)	(42.81)	(38.62)	(48.16)	(29.12)	(-7.64)	(45.01)	(22.71)	(24.31)	(25.64)	(25.80)	(19.81)	(-7.41)	(25.47)
High	0.616***	0.584***	0.587***	0.549***	0.501***	-0.115***	0.552***	0.550***	0.520***	0.522***	0.485***	0.434***	-0.116***	0.487***
	(28.68)	(30.27)	(29.65)	(28.63)	(29.65)	(-11.68)	(31.73)	(19.95)	(21.03)	(20.35)	(19.36)	(16.66)	(-11.66)	(19.54)
HML-G	-0.092***	-0.092***	-0.112***	-0.116***	-0.186***	-0.094***	-0.133***	-0.094***	-0.093***	-0.115***	-0.117***	-0.191***	-0.097***	-0.136***
	(-5.25)	(-6.73)	(-5.66)	(-7.28)	(-14.39)	(-4.95)	(-10.17)	(-5.45)	(-6.80)	(-5.85)	(-7.52)	(-15.29)	(-5.04)	(-10.87)
All	0.651***	0.637***	0.622***	0.587***	0.517***	-0.135***		0.588***	0.574***	0.558***	0.522***	0.452***	-0.136***	
	(29.96)	(31.75)	(30.47)	(37.49)	(29.80)	(-14.57)		(21.09)	(20.19)	(21.31)	(22.23)	(17.91)	(-14.47)	
Panel A2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.621***	0.601***	0.583***	0.526***	0.483***	-0.138***	0.534***	0.558***	0.538***	0.521***	0.460***	0.418***	-0.140***	0.468***
	(25.21)	(27.43)	(30.11)	(30.07)	(32.31)	(-8.50)	(35.27)	(19.55)	(19.72)	(21.98)	(18.34)	(17.00)	(-8.80)	(20.05)
2	0.679***	0.655***	0.635***	0.633***	0.626***	-0.053***	0.641***	0.615***	0.592***	0.570***	0.568***	0.561***	-0.054***	0.577***
	(29.76)	(29.57)	(38.39)	(39.72)	(40.66)	(-3.73)	(39.12)	(20.77)	(20.94)	(24.71)	(22.20)	(26.31)	(-3.83)	(23.94)
High	0.667***	0.668***	0.674***	0.677***	0.663***	-0.004	0.670***	0.604***	0.604***	0.610***	0.614***	0.599***	-0.005	0.606***
	(31.27)	(34.14)	(32.82)	(31.25)	(36.67)	(-0.34)	(34.75)	(20.68)	(22.79)	(20.55)	(21.42)	(25.82)	(-0.40)	(22.67)
HML-B	0.046*	0.066***	0.090***	0.152***	0.180***	0.134***	0.137***	0.046*	0.067***	0.089***	0.154***	0.182***	0.136***	0.138***
	(1.82)	(4.35)	(4.77)	(8.73)	(14.91)	(5.74)	(10.54)	(1.86)	(4.21)	(4.64)	(8.89)	(15.00)	(5.96)	(10.58)
All	0.651***	0.637***	0.622***	0.587***	0.517***	-0.135***		0.588***	0.574***	0.558***	0.522***	0.452***	-0.136***	
	(29.96)	(31.75)	(30.47)	(37.49)	(29.80)	(-14.57)		(21.09)	(20.19)	(21.31)	(22.23)	(17.91)	(-14.47)	

Panel B: Monthly FF6- and DGTW-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings

	FF6-adjusted ICC							DGTW-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel B1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.640***	0.610***	0.634***	0.601***	0.624***	-0.017	0.620***	0.060***	0.037***	0.041***	0.014**	0.040***	-0.020*	0.037***
	(21.97)	(23.52)	(22.39)	(25.06)	(23.44)	(-1.28)	(24.06)	(5.80)	(4.88)	(5.92)	(2.18)	(5.11)	(-1.78)	(7.40)
2	0.619***	0.617***	0.617***	0.575***	0.524***	-0.096***	0.581***	0.053***	0.069***	0.055***	0.033***	-0.012	-0.064***	0.035***
	(25.73)	(25.48)	(26.50)	(27.78)	(22.40)	(-7.28)	(27.68)	(5.61)	(8.13)	(8.06)	(3.51)	(-1.20)	(-7.10)	(4.68)
High	0.551***	0.522***	0.523***	0.484***	0.436***	-0.115***	0.488***	0.007	-0.004	-0.011*	-0.038***	-0.059***	-0.066***	-0.030***
	(20.55)	(21.55)	(20.96)	(19.88)	(16.87)	(-11.63)	(19.97)	(1.07)	(-1.17)	(-1.87)	(-6.10)	(-13.27)	(-7.97)	(-9.76)
HML-G	-0.089***	-0.088***	-0.111***	-0.117***	-0.188***	-0.099***	-0.132***	-0.053***	-0.041***	-0.052***	-0.051***	-0.099***	-0.046***	-0.067***
	(-5.40)	(-6.99)	(-5.63)	(-8.09)	(-17.74)	(-5.53)	(-11.58)	(-3.78)	(-4.91)	(-5.17)	(-5.67)	(-9.89)	(-2.87)	(-9.06)
All	0.587***	0.573***	0.561***	0.521***	0.452***	-0.135***		0.033***	0.021***	0.022***	-0.008**	-0.050***	-0.084***	
	(22.09)	(20.81)	(21.72)	(23.01)	(18.35)	(-14.78)		(7.73)	(4.59)	(5.26)	(-2.11)	(-16.28)	(-13.49)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.557***	0.539***	0.521***	0.460***	0.420***	-0.137***	0.470***	0.011	-0.001	-0.004	-0.045***	-0.068***	-0.079***	-0.039***
	(21.11)	(20.98)	(22.54)	(19.15)	(17.17)	(-9.07)	(20.67)	(1.00)	(-0.06)	(-0.57)	(-7.35)	(-13.39)	(-5.93)	(-9.85)
2	0.614***	0.592***	0.571***	0.565***	0.557***	-0.057***	0.575***	0.058***	0.040***	0.023***	0.020***	-0.002	-0.060***	0.025***
	(21.90)	(21.68)	(25.25)	(23.50)	(27.50)	(-3.98)	(25.03)	(7.61)	(4.47)	(3.85)	(3.96)	(-0.34)	(-7.60)	(6.33)
High	0.603***	0.604***	0.609***	0.612***	0.598***	-0.005	0.606***	0.027**	0.028***	0.035***	0.030***	0.026***	-0.001	0.030***
	(20.65)	(23.24)	(20.70)	(21.54)	(25.81)	(-0.42)	(22.82)	(2.55)	(3.33)	(3.97)	(2.81)	(3.74)	(-0.13)	(4.24)
HML-B	0.046*	0.064***	0.088***	0.152***	0.179***	0.133***	0.136***	0.017	0.029**	0.039***	0.075***	0.094***	0.077***	0.068***
	(1.82)	(4.30)	(4.69)	(8.55)	(14.61)	(5.82)	(10.30)	(0.88)	(2.11)	(2.84)	(5.45)	(10.22)	(4.18)	(6.68)
All	0.587***	0.573***	0.561***	0.521***	0.452***	-0.135***		0.033***	0.021***	0.022***	-0.008**	-0.050***	-0.084***	
	(22.09)	(20.81)	(21.72)	(23.01)	(18.35)	(-14.78)		(7.73)	(4.59)	(5.26)	(-2.11)	(-16.28)	(-13.49)	

Figure 1: Implied Cost of Capital of Portfolios Sorted by ESG Rating

In Graph (a), at the end of month t, stocks are sorted into quintiles according to their ESG ratings, with Quintile 1 (Quintile 5) comprising the bottom (top) quintile of stocks based on the ESG rating. For each of the five portfolios, we compute the value-weighted implied cost of capital (ICC) in month $t+1$ and rebalance the portfolios at the end of month $t+1$. We compute the ICC for each stock-month following Hou et al. (2012) and Pástor et al. (2022), and plot the time-series averages of the monthly ICCs for each of the five portfolios, as well as the Newey-West adjusted 95% confidence intervals. Graphs (b) to (d) plot the CAPM-adjusted ICCs, Fama-French six-factor-adjusted ICCs (FF6) and characteristic-adjusted ICCs per Daniel et al. (1997) (DGTW).



Active Fund Management when ESG Matters

Online Appendix

Doron Avramov Si Cheng Andrea Tarelli

This Online Appendix presents the proofs and derivations, a calibration exercise, as well as the supplementary empirical results discussed in the paper.

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A Derivations

Before proceeding with the derivations, we briefly describe the economic setting. Following Kacperczyk et al. (2016), asset payoffs are expressed in matrix form

$$\boldsymbol{f} = \boldsymbol{\mu} + \boldsymbol{\Gamma z}, \tag{A.1}$$

where $\boldsymbol{f}$, $\boldsymbol{\mu}$, $\boldsymbol{z} \sim \mathcal{MN}(\mathbf{0}, \boldsymbol{\Sigma})$, and $\boldsymbol{\Sigma}$ are the matrix versions of f_i, μ_i, z_i and σ_i, respectively, while $\boldsymbol{\Gamma}$ is given by

$$\boldsymbol{\Gamma} = \begin{bmatrix} 1 & 0 & \cdots & 0 & b_1 \\ 0 & 1 & \cdots & 0 & b_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & b_{N-1} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}, \tag{A.2}$$

and its inverse is given by

$$\boldsymbol{\Gamma}^{-1} = \begin{bmatrix} 1 & 0 & \cdots & 0 & -b_1 \\ 0 & 1 & \cdots & 0 & -b_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & -b_{N-1} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}. \tag{A.3}$$

The risk factors can then be rewritten as

$$\boldsymbol{\mathcal{F}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{f} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z}. \tag{A.4}$$

A risk factor supply is denoted by $\bar{\mathcal{X}}_i + \mathcal{X}_i$, where $\bar{\mathcal{X}}_i$ is the mean supply and $\mathcal{X}_i \sim \mathcal{N}(0, \sigma_{\mathcal{X}i})$ is the random supply noise. While in the text, the supply noise $\sigma_{\mathcal{X}i}$ is assumed to be constant across assets, in the derivations that follow, we consider the general case of heterogeneous supply noise. Let $\left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)$ denote the supply vector of the risk factors, where $\boldsymbol{\mathcal{X}} \sim \mathcal{MN}(\mathbf{0}, \boldsymbol{\Sigma}_{\mathcal{X}})$, and let $\bar{\boldsymbol{x}} + \boldsymbol{x}$ denote the supply of the risky assets. It follows that $\bar{\boldsymbol{x}} + \boldsymbol{x} = \boldsymbol{\Gamma}^{-1}\left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)$.

It is assumed that each of the agents, conditional on the time-2 realization of the private signals η_{ij}, has mean-variance preferences, given by

$$U_{2j} = \mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j G_j, \tag{A.5}$$

where ρ is risk aversion, δ_j represents the preference for ESG with a higher value reflecting a stronger preference, $G_j = \sum_{i=1}^{N} q_{ij} g_i$ is the ESG score of the portfolio, W_j stands for the agent's terminal wealth that satisfies the budget constraint $W_j = W_{0j} + \sum_{i=1}^{N} q_{ij}\left(f_i - p_i\right) - \sum_{i=1}^{N} c_{ij}\left(S_{ij}\right)$, p_i is the price of the risky asset, and $\sum_{i=1}^{N} c_{ij}\left(S_{ij}\right)$ is the total cost of information acquisition, with $c_{ij}\left(S_{ij}\right)$ standing for the cost per risk factor i, characterized by a signal precision S_{ij}. The ESG preference parameter δ_j is assumed to be nonnegative and strictly positive for a nonzero measure of agents in the economy.

The time-1 expected utility is

$$U_{1j} = \mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j G_j\right]. \tag{A.6}$$

The equilibrium is derived by backward induction, first optimizing the portfolio allocation in period 2 and then optimizing the information acquisition in period 1.

Let $\boldsymbol{\mathcal{P}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{p}$ denote the vector of risk factor prices, and let $\boldsymbol{\mathcal{Q}}_j = \boldsymbol{\Gamma}'\boldsymbol{q}_j$ denote the positions in the risk factors. As $\boldsymbol{f} = \boldsymbol{\Gamma}\boldsymbol{\mathcal{F}}$, $\boldsymbol{p} = \boldsymbol{\Gamma}\boldsymbol{\mathcal{P}}$, and $\boldsymbol{q}_j' = \boldsymbol{\mathcal{Q}}_j'\boldsymbol{\Gamma}^{-1}$, the budget constraint becomes $W_j = rW_{0j} + \boldsymbol{\mathcal{Q}}_j'\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right) - \sum_{i=1}^{N} c_{ij}\left(S_{ij}\right)$, and the ESG scores of the risk factors are $\boldsymbol{\mathcal{G}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{g}$. Hence, the individual ESG score of a risk factor is $\mathcal{G}_i = g_i - b_i g_N$ for $i < N$ and $\mathcal{G}_N = g_N$. Assuming that the aggregate asset is green neutral, the risk factors and the corresponding risky assets have the same ESG profile, $\mathcal{G}_i = g_i$.

A.1 Solving for asset prices

The equilibrium asset prices clear the market. The time-2 vector of prices is conjectured to be

$$\boldsymbol{\mathcal{P}} = \frac{1}{r}\left(\boldsymbol{A} + \boldsymbol{B}\boldsymbol{z} + \boldsymbol{C}\boldsymbol{\mathcal{X}} + \boldsymbol{D}\boldsymbol{\mathcal{G}}\right). \tag{A.7}$$

Our aim is to find the price coefficients.

To start, market clearing requires that

$$\int \boldsymbol{\mathcal{Q}}_j \mathrm{d}j = \bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}. \tag{A.8}$$

Agent j acquires information represented by the collection of signals $\boldsymbol{\eta}_j$, which are received at time 2:

$$\boldsymbol{\eta}_j = \boldsymbol{z} + \boldsymbol{\varepsilon}_j, \qquad \boldsymbol{\varepsilon}_j \sim \mathcal{MN}\left(\mathbf{0}, \mathbf{S}_j^{-1}\right), \tag{A.9}$$

where $\mathbf{S}_j$ is a diagonal matrix with nonnegative elements S_{ij}. At time 1, the agent chooses S_{ij} to maximize

$$U_{1j} = \mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j \mathrm{E}_{2j}\left[G_j\right]\right]. \tag{A.10}$$

The signal from prices takes the form

$$\boldsymbol{\eta}_p = \boldsymbol{z} + \boldsymbol{\varepsilon}_p \qquad \boldsymbol{\varepsilon}_p \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_p\right), \tag{A.11}$$

where $\boldsymbol{\Sigma}_p$ is recovered below. In particular,

$$\begin{aligned}
\boldsymbol{\eta}_p &= \boldsymbol{B}^{-1}\left(\boldsymbol{\mathcal{P}}r - \boldsymbol{A} - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\\
&= \boldsymbol{B}^{-1}\left(\boldsymbol{B}\boldsymbol{z} + \boldsymbol{C}\boldsymbol{\mathcal{X}}\right)\\
&= \boldsymbol{z} + \underbrace{\boldsymbol{B}^{-1}\boldsymbol{C}\boldsymbol{\mathcal{X}}}_{\boldsymbol{\varepsilon}_p},
\end{aligned} \tag{A.12}$$

where $\boldsymbol{\varepsilon}_p \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_p\right)$ and $\boldsymbol{\Sigma}_p = \boldsymbol{B}^{-1}\boldsymbol{C}\boldsymbol{\Sigma}_{\mathcal{X}}\boldsymbol{C}'\boldsymbol{B}^{-1\prime}$ ($\boldsymbol{\Sigma}_p^{-1} = \boldsymbol{B}'\boldsymbol{C}^{-1\prime}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\boldsymbol{C}^{-1}\boldsymbol{B}$).

The posterior beliefs about $\boldsymbol{z}$ can then be represented by the normal density with moments

$$\hat{\boldsymbol{z}}_j = \hat{\boldsymbol{\Sigma}}_j\left(\mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p\right), \tag{A.13}$$

$$\hat{\boldsymbol{\Sigma}}_j^{-1} = \boldsymbol{\Sigma}^{-1} + \mathbf{S}_j + \boldsymbol{\Sigma}_p^{-1}. \tag{A.14}$$

As $\boldsymbol{\mathcal{F}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z}$, the time-2 conditional expected payoff of the risk factors is

$$\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_j. \tag{A.15}$$

The posterior distribution of the risk factor payoffs is then

$$\boldsymbol{\mathcal{F}} \sim \mathcal{N}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right], \mathrm{Var}_{2j}\left[\boldsymbol{\mathcal{F}}\right]\right), \tag{A.16}$$

where $\mathrm{Var}_{2j}\left[\boldsymbol{\mathcal{F}}\right] = \hat{\boldsymbol{\Sigma}}_j$. The time-2 portfolio that optimally invests in the risk factors is given by

$$\boldsymbol{\mathcal{Q}}_j = \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right). \tag{A.17}$$

From Equation (A.7), we obtain

$$\boldsymbol{\mathcal{X}} = \boldsymbol{C}^{-1}\left(\boldsymbol{\mathcal{P}}r - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{z} - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right) = \boldsymbol{C}^{-1}\boldsymbol{B}\left(\boldsymbol{\eta}_p - \boldsymbol{z}\right). \tag{A.18}$$

Aggregating through the equations above yields

$$\begin{aligned}
\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}} = \bar{\boldsymbol{\mathcal{Q}}} &= \int_j \boldsymbol{\mathcal{Q}}_j \mathrm{d}j \\
&= \int_j \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)\mathrm{d}j \\
&= \int_j \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \mathrm{E}_{2j}\left[\boldsymbol{z}\right] - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}} + \delta_j\boldsymbol{\mathcal{G}}\right)\mathrm{d}j \\
&= \frac{1}{\rho}\left(\int_j \left(\mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p\right)\mathrm{d}j + \left(\int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j\right)\boldsymbol{\mathcal{G}} + \left(\int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\mathrm{d}j\right)\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\right) \\
&= \frac{1}{\rho}\left(\bar{\mathbf{S}}\boldsymbol{z} + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p + \left(\int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j\right)\boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}}^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\right),
\end{aligned} \tag{A.19}$$

where $\bar{\boldsymbol{\Sigma}}^{-1} = \int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\mathrm{d}j$ is a matrix with diagonal elements $\bar{\sigma}_i^{-1} = \int_j \hat{\sigma}_{ij}^{-1}\mathrm{d}j$, and $\bar{\mathbf{S}} = \int_j \mathbf{S}_j\mathrm{d}j$. In deriving the last expression, it is assumed that the average noise of the private signals is zero. Then, substituting Equation (A.18) into Equation (A.19) leads to

$$\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{C}^{-1}\boldsymbol{B}\left(\boldsymbol{\eta}_p - \boldsymbol{z}\right) = \frac{1}{\rho}\left(\bar{\mathbf{S}}\boldsymbol{z} + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p + \left(\int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j\right)\boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}}^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\right). \tag{A.20}$$

By matching coefficients, we obtain

$$\begin{cases}
\bar{\boldsymbol{\mathcal{X}}} = \frac{1}{\rho}\bar{\boldsymbol{\Sigma}}^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A}\right) \\
\boldsymbol{C}^{-1}\boldsymbol{B} = \frac{1}{\rho}\left(\boldsymbol{\Sigma}_p^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\boldsymbol{B}\right) \\
-\boldsymbol{C}^{-1}\boldsymbol{B} = \frac{1}{\rho}\bar{\mathbf{S}} \\
\boldsymbol{D} = \bar{\boldsymbol{\Sigma}}\int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j.
\end{cases} \tag{A.21}$$

The price coefficients then follow:

$$\begin{cases} \boldsymbol{A} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} \\ \boldsymbol{B} = \bar{\boldsymbol{\Sigma}}\left(\boldsymbol{\Sigma}_p^{-1} + \bar{\mathbf{S}}\right) = \mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1} \\ \boldsymbol{C} = -\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \boldsymbol{\Sigma}_p^{-1}\bar{\mathbf{S}}^{-1}\right) \\ \boldsymbol{D} = \bar{\boldsymbol{\Sigma}}\int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j \mathrm{d}j \equiv \bar{\boldsymbol{\delta}}, \end{cases} \tag{A.22}$$

where $\bar{\boldsymbol{\delta}}$ is a diagonal matrix with i-th element equal to $\bar{\delta}_i = \bar{\sigma}_i \int_j \hat{\sigma}_{ij}^{-1}\delta_j \mathrm{d}j$. As $\boldsymbol{B}^{-1}\boldsymbol{C} = -\rho\bar{\mathbf{S}}^{-1}$, we obtain

$$\boldsymbol{\Sigma}_p = \boldsymbol{B}^{-1}\boldsymbol{C}\boldsymbol{\Sigma}_{\mathcal{X}}\boldsymbol{C}'\boldsymbol{B}^{-1\prime} = \rho^2\bar{\mathbf{S}}^{-1}\boldsymbol{\Sigma}_{\mathcal{X}}\bar{\mathbf{S}}^{-1}. \tag{A.23}$$

It follows that $\boldsymbol{\Sigma}_p^{-1} = \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}$ and $\boldsymbol{C} = -\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)$. Thus, the diagonal elements of $\bar{\boldsymbol{\Sigma}}^{-1} = \boldsymbol{\Sigma}^{-1} + \bar{\mathbf{S}} + \boldsymbol{\Sigma}_p^{-1}$ can be written as

$$\bar{\sigma}_i^{-1} = \sigma_i^{-1} + \bar{S}_i + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}. \tag{A.24}$$

Next, the vector of risk factor prices (multiplied by the gross rate) is given by

$$\boldsymbol{\mathcal{P}}r = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} - \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} + \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}. \tag{A.25}$$

The terms of the diagonal matrix $\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}$ are all positive, expressed by $1 - \sigma_i^{-1}/\left(\sigma_i^{-1} + \bar{S}_i + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)$. Using the relations $\boldsymbol{\mathcal{P}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{p}$ and $\boldsymbol{\mathcal{X}} = \boldsymbol{\Gamma}\boldsymbol{x}$, the equilibrium asset prices are then given by

$$\boldsymbol{p}r = \boldsymbol{\mu} - \rho\boldsymbol{\Gamma}\bar{\boldsymbol{\Sigma}}\boldsymbol{\Gamma}\bar{\boldsymbol{x}} + \boldsymbol{\Gamma}\left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} - \rho\boldsymbol{\Gamma}\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\Gamma}\boldsymbol{x} + \boldsymbol{\Gamma}\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}. \tag{A.26}$$

Proposition 1 follows by substituting $\boldsymbol{\Gamma}$ from Equation (A.2).

A.2 Solving for information decisions

Our aim is to derive the time-1 expected utility. Then, the information decision is based on equating the marginal benefit from information acquisition to the marginal cost. To start, the agent's wealth can be expressed as

$$W_j = rW_{0j} + \frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right) - c_j\left(\mathbf{S}_j\right). \tag{A.27}$$

Then, the time-1 expected utility is

$$\begin{aligned} U_{1j} = \mathrm{E}_{1j}&\left[\mathrm{E}_{2j}\left[rW_{0j} + \frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\ &- \frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[rW_{0j} + \frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\ &+ \frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}\right] - c_j\left(\mathbf{S}_j\right), \\ = rW_{0j} &+ \mathrm{E}_{1j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] \\ &- \frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\ &+ \frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\right]\boldsymbol{\mathcal{G}} - c_j\left(\mathbf{S}_j\right). \end{aligned} \tag{A.28}$$

To further characterize the above expression, we use Equations (A.4) and (A.25) to rewrite the net payoff as

$$\begin{aligned}
\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}} r &= \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z} - \left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} - \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} + \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) \\
&= \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} \\
&= \mathbf{w} + \mathbf{V}^{\frac{1}{2}}\mathbf{u},
\end{aligned} \tag{A.29}$$

where $\mathbf{u} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, $\mathbf{w} = \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}$, $\mathbf{V}^{\frac{1}{2}}\mathbf{u} = \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}$, and $\mathbf{V}$ is given by

$$\begin{aligned}
\mathbf{V} &= \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}} + \rho^2\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\Sigma}_{\mathcal{X}}\left(\mathbf{I} + \frac{1}{\rho^2}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\bar{\boldsymbol{\Sigma}}, \\
&= \bar{\boldsymbol{\Sigma}}\left(\boldsymbol{\Sigma}^{-1} + \rho^2\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\Sigma}_{\mathcal{X}}\left(\mathbf{I} + \frac{1}{\rho^2}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\right)\bar{\boldsymbol{\Sigma}}, \\
&= \bar{\boldsymbol{\Sigma}}\left(\boldsymbol{\Sigma}^{-1} + \rho^2\boldsymbol{\Sigma}_{\mathcal{X}} + \bar{\mathbf{S}} + \underbrace{\bar{\mathbf{S}} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}}_{\boldsymbol{\Sigma}_p^{-1}}\right)\bar{\boldsymbol{\Sigma}}, \\
&= \bar{\boldsymbol{\Sigma}}\left(\rho^2\boldsymbol{\Sigma}_{\mathcal{X}} + \bar{\mathbf{S}} + \bar{\boldsymbol{\Sigma}}^{-1}\right)\bar{\boldsymbol{\Sigma}}.
\end{aligned} \tag{A.30}$$

The matrix V is diagonal with elements $V_{ii} = \bar{\sigma}_i\left(1 + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i\right)$.

The time-2 expected net payoff is $\mathrm{E}_{2j}[\boldsymbol{\mathcal{F}}] - \boldsymbol{\mathcal{P}} r = \mathrm{E}_{2j}[\boldsymbol{\mathcal{F}}] - \boldsymbol{\mathcal{F}} + \boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}} r$, while the time-1 variance is

$$\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}[\boldsymbol{\mathcal{F}}] - \boldsymbol{\mathcal{P}} r\right] = \mathrm{Var}_{1j}\left[\mathrm{E}_{2j}[\boldsymbol{\mathcal{F}}] - \boldsymbol{\mathcal{F}}\right] + \mathrm{Var}_{1j}\left[\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}} r\right] + 2\mathrm{Cov}_{1j}\left[\mathrm{E}_{2j}[\boldsymbol{\mathcal{F}}] - \boldsymbol{\mathcal{F}}, \boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}} r\right]. \tag{A.31}$$

We solve each of the variance components.

From Equations (A.4) and (A.15), we obtain

$$\begin{aligned}
\mathrm{E}_{2j}[\boldsymbol{\mathcal{F}}] - \boldsymbol{\mathcal{F}} &= \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{\Sigma}}_j\mathbf{S}_j(\boldsymbol{z} + \boldsymbol{\varepsilon}_j) + \hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}_p^{-1}(\boldsymbol{z} + \boldsymbol{\varepsilon}_p) - \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{z} \\
&= \hat{\boldsymbol{\Sigma}}_j\left(\left(\mathbf{S}_j + \boldsymbol{\Sigma}_p^{-1} - \hat{\boldsymbol{\Sigma}}_j^{-1}\right)\boldsymbol{z} + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p\right) \\
&= \hat{\boldsymbol{\Sigma}}_j\left(-\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p\right).
\end{aligned} \tag{A.32}$$

The time-1 expected value of the above expression is zero. Then, as $\boldsymbol{z}$, $\boldsymbol{\varepsilon}_j$, and $\boldsymbol{\varepsilon}_p$ are independent, the time-1 variance is equal to

$$\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}[\boldsymbol{\mathcal{F}}] - \boldsymbol{\mathcal{F}}\right] = \hat{\boldsymbol{\Sigma}}_j\underbrace{\left(\boldsymbol{\Sigma}^{-1} + \mathbf{S}_j + \boldsymbol{\Sigma}_p^{-1}\right)}_{\hat{\boldsymbol{\Sigma}}_j^{-1}}\hat{\boldsymbol{\Sigma}}_j' = \hat{\boldsymbol{\Sigma}}_j. \tag{A.33}$$

From Equation (A.29), we obtain $\mathrm{Var}_{1j}[\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}} r] = \mathbf{V}$. To solve for the third term in Equation (A.31), we first express the net payoff as

$$\begin{aligned}
\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}} r &= \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z} - \boldsymbol{A} - \boldsymbol{B}(\boldsymbol{z} + \boldsymbol{\varepsilon}_p) - \boldsymbol{D}\boldsymbol{\mathcal{G}} \\
&= \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z} - \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)(\boldsymbol{z} + \boldsymbol{\varepsilon}_p) - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} \\
&= \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{\varepsilon}_p - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}.
\end{aligned} \tag{A.34}$$

Then, the third term is

$$\begin{aligned}
\mathrm{Cov}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{F}},\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right] &= \mathrm{Cov}_1\left[\hat{\boldsymbol{\Sigma}}_j\left(-\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\mathbf{S}_j\boldsymbol{\varepsilon}_j+\boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p\right),\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}-\left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{\varepsilon}_p\right]\\
&= \mathrm{Cov}_1\left[-\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p,\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}-\left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{\varepsilon}_p\right]\\
&= -\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}^{-1}\boldsymbol{\Sigma}\boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}}-\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}_p^{-1}\boldsymbol{\Sigma}_p\left(\mathbf{I}-\boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}}\right)\\
&= -\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}}-\hat{\boldsymbol{\Sigma}}_j\left(\mathbf{I}-\boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}}\right)\\
&= -\hat{\boldsymbol{\Sigma}}_j.
\end{aligned}\tag{A.35}$$

Aggregating through the three terms, the time-1 variance in Equation (A.31) is

$$\begin{aligned}
\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right] &= \hat{\boldsymbol{\Sigma}}_j+\mathbf{V}-2\hat{\boldsymbol{\Sigma}}_j=\mathbf{V}-\hat{\boldsymbol{\Sigma}}_j\\
&= \bar{\boldsymbol{\Sigma}}\left(\rho^2\boldsymbol{\Sigma}_{\mathcal{X}}+\bar{\mathbf{S}}+\bar{\boldsymbol{\Sigma}}^{-1}\right)\bar{\boldsymbol{\Sigma}}-\hat{\boldsymbol{\Sigma}}_j,
\end{aligned}\tag{A.36}$$

which is a diagonal matrix with elements

$$\left(\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right]\right)_{ii}=\bar{\sigma}_i\left(1+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i\right)-\hat{\sigma}_{ij}=\left(\bar{\sigma}_i-\hat{\sigma}_{ij}\right)+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2.\tag{A.37}$$

The time-1 distribution of the expected excess payoff is

$$\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\sim\mathcal{MN}\left(\mathbf{w},\mathbf{V}-\hat{\boldsymbol{\Sigma}}_j\right).\tag{A.38}$$

Equation (A.28) can be rewritten as

$$\begin{aligned}
U_{1j} &= rW_{0j}+\frac{1}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right]\\
&\quad+\frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right]\\
&\quad-\frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right]\\
&\quad+\frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\right]\boldsymbol{\mathcal{G}}\\
&\quad+\frac{\delta_j^2}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}-c_j\left(\boldsymbol{S}_j\right)\\
&= rW_{0j}+\frac{1}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right]\\
&\quad+\frac{\delta_j}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right]\\
&\quad-\frac{1}{2\rho}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right]\\
&\quad+\frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\right]\boldsymbol{\mathcal{G}}\\
&\quad+\frac{\delta_j^2}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}-c_j\left(\boldsymbol{S}_j\right).
\end{aligned}\tag{A.39}$$

Then, the first term in Equation (A.39) depends on

$$\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right]=\mathrm{E}_{1j}\left[\boldsymbol{m}_1'\boldsymbol{m}_1\right], \tag{A.40}$$

where $\boldsymbol{m}_1=\hat{\boldsymbol{\Sigma}}_j^{-\frac{1}{2}}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)$, $\mathrm{E}_{1j}\left[\boldsymbol{m}_1\right]=\hat{\boldsymbol{\Sigma}}_j^{-\frac{1}{2}}\mathbf{w}$, and $\mathrm{Var}_{1j}\left[\boldsymbol{m}_1\right]=\hat{\boldsymbol{\Sigma}}_j^{-\frac{1}{2}}\left(\mathbf{V}-\hat{\boldsymbol{\Sigma}}_j\right)\hat{\boldsymbol{\Sigma}}_j^{-\frac{1}{2}}=\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{V}-\mathbf{I}$. Then $\boldsymbol{m}_1\sim\mathcal{MN}\left(\hat{\boldsymbol{\Sigma}}_j^{-\frac{1}{2}}\mathbf{w},\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{V}-\mathbf{I}\right)$. Hence,

$$\begin{aligned}
&\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right]\\
&\quad=\mathrm{E}_{1j}\left[\boldsymbol{m}_1'\boldsymbol{m}_1\right]=\mathrm{tr}\left(\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{V}-\mathbf{I}\right)+\mathbf{w}'\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{w}\\
&\quad=\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\underbrace{\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i}_{w_i}\right)^2\right)\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)-N,
\end{aligned} \tag{A.41}$$

where $w_i=\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i$. The second term in Equation (A.39) is proportional to $\mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right]=\mathbf{w}$, while the third term depends on

$$\begin{aligned}
&\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right]\\
&\quad=\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\underbrace{\mathrm{Var}_{2j}\left[\boldsymbol{\mathcal{F}}\right]}_{\hat{\boldsymbol{\Sigma}}_j}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)\right]\\
&\quad=\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)\right]\\
&\quad=\mathrm{tr}\left(\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{V}-\mathbf{I}\right)+\left(\mathbf{w}+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{w}+\delta_j\boldsymbol{\mathcal{G}}\right)\\
&\quad=\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_x}\right)-N.
\end{aligned} \tag{A.42}$$

The fourth term is proportional to

$$\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\right]=\mathbf{w}'\hat{\boldsymbol{\Sigma}}_j^{-1}. \tag{A.43}$$

The time-1 expected utility in Equation (A.39) is then given by

$$\begin{aligned}
U_{1j}&=rW_{0j}\\
&\quad+\frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{N}{\rho}\\
&\quad+\frac{\delta_j}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{w}\\
&\quad-\frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)+\frac{N}{2\rho}\\
&\quad+\frac{\delta_j}{\rho}\mathbf{w}'\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}+\frac{\delta_j^2}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}-c_j\left(\boldsymbol{S}_j\right)\\
&=rW_{0j}\\
&\quad+\frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{N}{\rho}
\end{aligned}$$

$$
\begin{aligned}
&+\sum_{i=1}^{N}2\frac{\delta_j}{\rho}\mathcal{G}_i\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\\
&-\frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)+\frac{N}{2\rho}\\
&+\frac{\delta_j^2}{\rho}\sum_{i=1}^{N}\mathcal{G}_i^2\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)-\sum_{i=1}^{N}c_{ij}\left(S_{ij}\right)\\
=&\ \text{constant}+\sum_{i=1}^{N}\psi_{ij}S_{ij}-\sum_{i=1}^{N}c_{ij}\left(S_{ij}\right), \qquad \text{(A.44)}
\end{aligned}
$$

where

$$
\begin{aligned}
2\rho\psi_{ij}&=\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+2\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)^2+4\delta_j\mathcal{G}_i\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)-\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i+\delta_j\mathcal{G}_i\right)^2+2\delta_j^2\mathcal{G}_i^2\\
&=\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+2\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2+2\left(\bar{\delta}_i\mathcal{G}_i\right)^2-4\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\bar{\delta}_i\mathcal{G}_i+4\delta_j\mathcal{G}_i\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-4\delta_j\bar{\delta}_i\mathcal{G}_i^2-\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2\\
&=-\left(\bar{\delta}_i\mathcal{G}_i\right)^2-\left(\delta_j\mathcal{G}_i\right)^2+2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\bar{\delta}_i\mathcal{G}_i-2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\delta_j\mathcal{G}_i+2\bar{\delta}_i\delta_j\mathcal{G}_i^2+2\delta_j^2\mathcal{G}_i^2\\
&=\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2-2\delta_j\bar{\delta}_i\mathcal{G}_i^2+\left(\bar{\delta}_i\mathcal{G}_i\right)^2+\left(\delta_j\mathcal{G}_i\right)^2-2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\bar{\delta}_i\mathcal{G}_i+2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\delta_j\mathcal{G}_i\\
&=\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2+\left(\delta_j-\bar{\delta}_i\right)^2\mathcal{G}_i^2+2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\\
&=\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)^2. \qquad \text{(A.45)}
\end{aligned}
$$

Accounting for the constraint $S_{ij}\geq 0$, the optimal signal precision is given by

$$
S_{ij}=\max\ \left[0,s|c_{ij}'\left(s\right)=\psi_{ij}\right]. \qquad \text{(A.46)}
$$

A.3 Sensitivity of the optimal aggregate signal precision to the ESG score

Taking the derivative of ψ_{ij} in Equation (A.45) with respect to g_i, we obtain

$$
\begin{aligned}
\frac{\partial\psi_{ij}}{\partial g_i}=&\frac{\bar{\sigma}_i^2\frac{\partial\bar{S}_i}{\partial g_i}+\left(1+2\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i+2\rho\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\left(\delta_j-\bar{\delta}_i\right)g_i\right)\right)\frac{\partial\bar{\sigma}_i}{\partial g_i}}{2\rho}\\
&+\frac{\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\left(\delta_j-\bar{\delta}_i\right)g_i\right)\left(\delta_j-\bar{\delta}_i\right)}{\rho}. \qquad \text{(A.47)}
\end{aligned}
$$

It then follows that

$$
\frac{\partial\bar{\sigma}_i}{\partial g_i}=\frac{\partial}{\partial g_i}\left(\sigma_i^{-1}+\bar{S}_i+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)^{-1}=-\left(\sigma_i^{-1}+\bar{S}_i+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)^{-2}\left(1+\frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\frac{\partial\bar{S}_i}{\partial g_i}. \qquad \text{(A.48)}
$$

When $c_{ij}\left(s\right)=\kappa s^2$ for all assets and agents, the optimal signal precision is strictly positive and equal to $S_{ij}=\frac{\psi_{ij}}{2\kappa}$. Then,

$$
\begin{aligned}
\frac{\partial S_{ij}}{\partial g_i}=&-\bar{\sigma}_i^2\frac{\left(2\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i+2\rho\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\left(\delta_j-\bar{\delta}_i\right)g_i\right)\right)\left(1+\frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)+\frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}}{2\rho\kappa}\frac{\partial\bar{S}_i}{\partial g_i}\\
&+\frac{\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\left(\delta_j-\bar{\delta}_i\right)g_i}{\rho\kappa}\left(\delta_j-\bar{\delta}_i\right). \qquad \text{(A.49)}
\end{aligned}
$$

Integrating across agents allows one to obtain the sensitivity of the average signal precision with respect to the ESG score

$$\frac{\partial \bar{S}_i}{\partial g_i}=\frac{\frac{\rho\bar{\sigma}_i\bar{\mathcal{X}}_i}{\rho\kappa}\left(\int_j\delta_j\mathrm{d}j-\bar{\delta}_i\right)+\frac{g_i}{\rho\kappa}\int_j\left(\delta_j-\bar{\delta}_i\right)^2\mathrm{d}j}{1+\bar{\sigma}_i^2\frac{\left(2\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i+2\rho\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\left(\int_j\delta_j\mathrm{d}j-\bar{\delta}_i\right)g_i\right)\right)\left(1+\frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)+\frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}}{2\rho\kappa}}. \tag{A.50}$$

Assuming $\bar{\delta}_i=\int_j\delta_j\mathrm{d}j$, it follows that $\int_j\left(\delta_j-\bar{\delta}_i\right)\mathrm{d}j=0$, while $\sigma_\delta=\int_j\left(\delta_j-\bar{\delta}_i\right)^2\mathrm{d}j$ represents the variance of ESG preferences across agents. The sensitivity of the average signal precision can then be expressed as

$$\frac{\partial \bar{S}_i}{\partial g_i}=\frac{\sigma_\delta}{\rho\kappa+\left(\left(\rho^2\left(\sigma_{\mathcal{X}i}+\bar{\mathcal{X}}_i^2\right)+\bar{S}_i\right)\left(1+\frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i^2}g_i, \tag{A.51}$$

where the denominator is a positive quantity. Multiplying both sides by $\operatorname{sign}(g_i)$, the derivative can be rewritten as

$$\frac{\partial \bar{S}_i}{\partial |g_i|}=\frac{\sigma_\delta}{\rho\kappa+\left(\left(\rho^2\left(\sigma_{\mathcal{X}i}+\bar{\mathcal{X}}_i^2\right)+\bar{S}_i\right)\left(1+\frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i^2}|g_i|. \tag{A.52}$$

A.4 Price informativeness

We can evaluate the price informativeness for risk factor i as follows:

$$\begin{aligned}
\mathcal{PI}_i &= \frac{\operatorname{Cov}\left[\mathcal{F}_i,\mathcal{P}_i\right]}{\operatorname{Std}\left[\mathcal{P}_i\right]}=\frac{\operatorname{Cov}\left[\mathcal{F}_i,\mathcal{P}_i r\right]}{\operatorname{Std}\left[\mathcal{P}_i r\right]}\\
&=\frac{\operatorname{Cov}\left[z_i,\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right]}{\operatorname{Std}\left[\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right]}\\
&=\frac{\sigma_i-\bar{\sigma}_i}{\sqrt{\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)^2\sigma_i+\rho^2\bar{\sigma}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2\sigma_{\mathcal{X}i}}}\\
&=\frac{\sigma_i}{\sqrt{\sigma_i+\rho^2\frac{\sigma_{\mathcal{X}i}}{\bar{S}_i^2}}}.
\end{aligned} \tag{A.53}$$

When the average signal precision of the risk factor, $\bar{S}_i$, approaches zero, the risk factor price does not provide any information about the random payoff. In addition, price informativeness monotonically increases with the average signal precision, converging to $\sqrt{\sigma_i}$ as $\bar{S}_i$ grows arbitrarily large. The asset-level price informativeness is

$$\begin{aligned}
\mathrm{PI}_i &= \frac{\operatorname{Cov}\left[f_i,p_i\right]}{\operatorname{Std}\left[p_i\right]}=\frac{\operatorname{Cov}\left[\mathcal{F}_i+b_i\mathcal{F}_N,\mathcal{P}_i r+b_i\mathcal{P}_N r\right]}{\operatorname{Std}\left[\mathcal{P}_i r+b_i\mathcal{P}_N r\right]}\\
&=\frac{\operatorname{Cov}\left[z_i,\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right]+b_i^2\operatorname{Cov}\left[z_N,\left(1-\frac{\bar{\sigma}_N}{\sigma_N}\right)z_N-\rho\bar{\sigma}_N\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)\mathcal{X}_N\right]}{\operatorname{Std}\left[\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i+b_i\left(\left(1-\frac{\bar{\sigma}_N}{\sigma_N}\right)z_N-\rho\bar{\sigma}_N\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)\mathcal{X}_N\right)\right]}\\
&=\frac{\sigma_i-\bar{\sigma}_i+b_i^2\left(\sigma_N-\bar{\sigma}_N\right)}{\sqrt{\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)^2\sigma_i+\rho^2\bar{\sigma}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2\sigma_{\mathcal{X}i}+b_i^2\left(\left(1-\frac{\bar{\sigma}_N}{\sigma_N}\right)^2\sigma_N+\rho^2\bar{\sigma}_N^2\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)^2\sigma_{\mathcal{X}N}\right)}}\\
&=\frac{\sigma_i-\bar{\sigma}_i+b_i^2\left(\sigma_N-\bar{\sigma}_N\right)}{\sqrt{\bar{\sigma}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2\left(\bar{S}_i^2\sigma_i+\rho^2\sigma_{\mathcal{X}i}\right)+b_i^2\bar{\sigma}_N^2\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)^2\left(\bar{S}_N^2\sigma_N+\rho^2\sigma_{\mathcal{X}N}\right)}}
\end{aligned}$$

$$
\begin{aligned}
&= \frac{\frac{1}{\sigma_i^{-1}} - \frac{1}{\sigma_i^{-1}+\bar{S}_i+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}} + b_i^2\left(\frac{1}{\sigma_N^{-1}} - \frac{1}{\sigma_N^{-1}+\bar{S}_N+\frac{\bar{S}_N^2}{\rho^2\sigma_{\mathcal{X}N}}}\right)}{\sqrt{\bar{\sigma}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2\left(\bar{S}_i^2\sigma_i+\rho^2\sigma_{\mathcal{X}i}\right) + b_i^2\bar{\sigma}_N^2\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)^2\left(\bar{S}_N^2\sigma_N+\rho^2\sigma_{\mathcal{X}N}\right)}} \\
&= \frac{\sigma_i\bar{\sigma}_i\bar{S}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right) + b_i^2\sigma_N\bar{\sigma}_N\bar{S}_N\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)}{\sqrt{\left(\sigma_i+\rho^2\frac{\sigma_{\mathcal{X}i}}{\bar{S}_i^2}\right)\bar{\sigma}_i^2\bar{S}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2 + b_i^2\left(\sigma_N+\rho^2\frac{\sigma_{\mathcal{X}N}}{\bar{S}_N^2}\right)\bar{\sigma}_N^2\bar{S}_N^2\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)^2}} \\
&= \frac{\sigma_i\zeta_i + b_i^2\sigma_N\zeta_N}{\sqrt{\left(\sigma_i+\rho^2\frac{\sigma_{\mathcal{X}i}}{\bar{S}_i^2}\right)\zeta_i^2 + b_i^2\left(\sigma_N+\rho^2\frac{\sigma_{\mathcal{X}N}}{\bar{S}_N^2}\right)\zeta_N^2}}. \qquad \text{(A.54)}
\end{aligned}
$$

A.5 Portfolio positions and ESG profile

We first derive the portfolio that optimally invests in the risk factors. Substituting Equations (A.13) and (A.15) into Equation (A.17), the optimal portfolio is given by

$$
\begin{aligned}
\boldsymbol{\mathcal{Q}}_j &= \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{\Sigma}}_j\left(\mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p\right) - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p - \hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{P}}r + \delta_j\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) + \mathbf{S}_j\left(\boldsymbol{z}+\boldsymbol{\varepsilon}_j\right) + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\left(\boldsymbol{z}-\rho\bar{\mathbf{S}}^{-1}\boldsymbol{\mathcal{X}}\right) + \delta_j\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}} + \left(\mathbf{S}_j - \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right) + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\boldsymbol{z}\right. \\
&\quad \left. + \left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) - \frac{1}{\rho}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} + \mathbf{S}_j\boldsymbol{\varepsilon}_j\right). \qquad \text{(A.55)}
\end{aligned}
$$

The unconditional expectation of the portfolio is

$$
\mathrm{E}\left[\boldsymbol{\mathcal{Q}}_j\right] = \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right). \qquad \text{(A.56)}
$$

From Equations (A.19) and (A.22), the cross-agent average portfolio is

$$
\begin{aligned}
\bar{\boldsymbol{\mathcal{Q}}} &= \int_j \boldsymbol{\mathcal{Q}}_j \mathrm{d}j \\
&= \frac{1}{\rho}\left(\bar{\boldsymbol{\Sigma}}^{-1}\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \bar{\mathbf{S}}\boldsymbol{z} + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p - \bar{\boldsymbol{\Sigma}}^{-1}\boldsymbol{\mathcal{P}}r + \bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\bar{\boldsymbol{\Sigma}}^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right) + \bar{\mathbf{S}}\boldsymbol{z} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\left(\boldsymbol{z}-\rho\bar{\mathbf{S}}^{-1}\boldsymbol{\mathcal{X}}\right)\right). \qquad \text{(A.57)}
\end{aligned}
$$

Its unconditional expectation is $\mathrm{E}\left[\bar{\boldsymbol{\mathcal{Q}}}\right] = \bar{\boldsymbol{\mathcal{X}}}$. The difference between the risk-factor portfolio of investor j in Equation (A.17) and the average portfolio is

$$
\begin{aligned}
\boldsymbol{\mathcal{Q}}_j - \bar{\boldsymbol{\mathcal{Q}}} &= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{\mathcal{P}}r\right) + \left(\mathbf{S}_j - \bar{\mathbf{S}}\right)\boldsymbol{z} + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \left(\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j - \bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \left(\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j - \bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)
\end{aligned}
$$

$$= \frac{1}{\rho}\left(\left(\hat{\mathbf{\Sigma}}_j^{-1} - \bar{\mathbf{\Sigma}}^{-1}\right)\left(\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \left(\hat{\mathbf{\Sigma}}_j^{-1}\delta_j - \bar{\mathbf{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)$$

$$= \frac{1}{\rho}\left(\left(\hat{\mathbf{\Sigma}}_j^{-1} - \bar{\mathbf{\Sigma}}^{-1}\right)\left(\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \hat{\mathbf{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right), \tag{A.58}$$

where the second equality follows from $\hat{\mathbf{\Sigma}}_j^{-1} - \bar{\mathbf{\Sigma}}^{-1} = \mathbf{S}_j - \bar{\mathbf{S}}$ and $\boldsymbol{\mathcal{F}} = \mathbf{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z}$, while the third equality follows from Equation (A.29). The unconditional expectation of the difference is

$$\mathrm{E}\left[\boldsymbol{\mathcal{Q}}_j - \bar{\boldsymbol{\mathcal{Q}}}\right] = \left(\hat{\mathbf{\Sigma}}_j^{-1}\bar{\mathbf{\Sigma}} - \mathbf{I}\right)\bar{\boldsymbol{\mathcal{X}}} + \frac{1}{\rho}\hat{\mathbf{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}. \tag{A.59}$$

We next analyze the optimal portfolio of risky assets. As $\boldsymbol{q}_j = \mathbf{\Gamma}^{-1\prime}\boldsymbol{\mathcal{Q}}_j$, the expected portfolio positions are given by

$$\mathrm{E}\left[\boldsymbol{q}_j\right] = \mathbf{\Gamma}^{-1\prime}\hat{\mathbf{\Sigma}}_j^{-1}\bar{\mathbf{\Sigma}}\mathbf{\Gamma}\bar{\boldsymbol{x}} + \frac{1}{\rho}\mathbf{\Gamma}^{-1\prime}\hat{\mathbf{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}$$

$$= \mathbf{\Gamma}^{-1\prime}\begin{bmatrix} \vdots \\ \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(\bar{x}_i + b_i\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho}\hat{\sigma}_{ij}g_i \\ \vdots \\ \frac{\hat{\sigma}_{Nj}^{-1}}{\bar{\sigma}_N^{-1}}\bar{x}_N \end{bmatrix}$$

$$= \begin{bmatrix} \vdots \\ \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(\bar{x}_i + b_i\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho}\hat{\sigma}_{ij}g_i \\ \vdots \\ \frac{\hat{\sigma}_{Nj}^{-1}}{\bar{\sigma}_N^{-1}}\bar{x}_N - \sum_{k=1}^{N-1} b_k\left(\frac{\hat{\sigma}_{kj}^{-1}}{\bar{\sigma}_k^{-1}}\left(\bar{x}_k + b_k\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_k}{\rho}\hat{\sigma}_{kj}g_k\right) \end{bmatrix}. \tag{A.60}$$

It then follows that

$$\begin{cases} \mathrm{E}\left[q_{ij}\right] = \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(\bar{x}_i + b_i\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho}\hat{\sigma}_{ij}g_i \quad i = 1, \ldots, N-1 \\ \mathrm{E}\left[q_{Nj}\right] = \frac{\hat{\sigma}_{Nj}^{-1}}{\bar{\sigma}_N^{-1}}\bar{x}_N - \sum_{k=1}^{N-1} b_k\mathrm{E}\left[q_{kj}\right]. \end{cases} \tag{A.61}$$

The expected portfolio positions in excess of the market counterparts are

$$\mathrm{E}\left[\boldsymbol{q}_j - \bar{\boldsymbol{q}}\right] = \mathbf{\Gamma}^{-1\prime}\left(\hat{\mathbf{\Sigma}}_j^{-1}\bar{\mathbf{\Sigma}} - \mathbf{I}\right)\bar{\boldsymbol{\mathcal{X}}} + \frac{1}{\rho}\hat{\mathbf{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}$$

$$= \mathbf{\Gamma}^{-1\prime}\begin{bmatrix} \vdots \\ \left(\frac{\bar{\sigma}_i}{\hat{\sigma}_{ij}} - 1\right)\left(\bar{x}_i + b_i\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho}\hat{\sigma}_{ij}^{-1}g_i \\ \vdots \\ \left(\frac{\bar{\sigma}_N}{\hat{\sigma}_{Nj}} - 1\right)\bar{x}_N \end{bmatrix}$$

$$= \begin{bmatrix} \vdots \\ \left(\frac{\bar{\sigma}_i}{\hat{\sigma}_{ij}} - 1\right)\left(\bar{x}_i + b_i\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho}\hat{\sigma}_{ij}^{-1}g_i \\ \vdots \\ \left(\frac{\bar{\sigma}_N}{\hat{\sigma}_{Nj}} - 1\right)\bar{x}_N - \sum_{i=1}^{N-1} b_i\left(\left(\frac{\bar{\sigma}_i}{\hat{\sigma}_{ij}} - 1\right)\left(\bar{x}_i + b_i\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho}\hat{\sigma}_{ij}^{-1}g_i\right) \end{bmatrix}. \tag{A.62}$$

Then,

$$\begin{cases} \mathrm{E}\left[q_{ij}-\bar{q}_i\right]=\left(S_{ij}-\bar{S}_i\right)\bar{\sigma}_i\left(\bar{x}_i+b_i\bar{x}_N\right)+\frac{\delta_j-\bar{\delta}_i}{\rho}\hat{\sigma}_{ij}^{-1}g_i, & i=1,\ldots,N-1 \\ \mathrm{E}\left[q_{Nj}-\bar{q}_N\right]=\left(S_{Nj}-\bar{S}_N\right)\bar{\sigma}_N\bar{x}_N-\sum_{i=1}^{N-1}b_i\mathrm{E}\left[q_{ij}-\bar{q}_i\right]. \end{cases} \tag{A.63}$$

The first equation in Proposition 2 follows.

The expected ESG score of the portfolio is given by

$$\begin{aligned} \mathrm{E}\left[G_j\right] &= \mathrm{E}\left[\left(\boldsymbol{q}_j-\bar{\boldsymbol{q}}\right)'\boldsymbol{g}\right] \\ &= \mathrm{E}\left[\left(\boldsymbol{\mathcal{Q}}_j-\bar{\boldsymbol{\mathcal{Q}}}\right)'\boldsymbol{\mathcal{G}}\right] \\ &= \frac{1}{\rho}\mathrm{E}\left[\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1}-\bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right)+\mathbf{S}_j\boldsymbol{\varepsilon}_j+\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\boldsymbol{\mathcal{G}}\right] \\ &= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1}-\bar{\boldsymbol{\Sigma}}^{-1}\right)\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\boldsymbol{\mathcal{G}} \\ &= \sum_{i=1}^{N}\bar{\mathcal{X}}_i\left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}-1\right)\mathcal{G}_i+\frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i^2 \\ &= \sum_{i=1}^{N}\left(\bar{x}_i+b_i\bar{x}_N\right)\left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}-1\right)g_i+\rho^{-1}\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)g_i^2. \end{aligned} \tag{A.64}$$

A.6 Expected utility loss from following a suboptimal strategy and information acquisition policy

If agent j follows the strategy and the information decision that are optimal for agent k, its terminal wealth can be expressed as

$$W_{j|k}=rW_{0j}+\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)-c_j\left(\mathbf{S}_k\right). \tag{A.65}$$

Then, the time-1 expected utility is

$$\begin{aligned} U_{1j|k} &= rW_{0j}+\mathrm{E}_{1j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right] \\ &\quad-\frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right] \\ &\quad+\frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\right]\boldsymbol{\mathcal{G}}-c_j\left(\mathbf{S}_k\right) \\ &= rW_{0j}+\frac{1}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right] \\ &\quad+\frac{\delta_k}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_k^{-1}\mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right] \\ &\quad-\frac{1}{2\rho}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right] \\ &\quad+\frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\right]\boldsymbol{\mathcal{G}} \\ &\quad+\frac{\delta_j\delta_k}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_k^{-1}\boldsymbol{\mathcal{G}}-c_j\left(\boldsymbol{S}_k\right) \\ &= rW_{0j} \\ &\quad+\frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1}+S_{ik}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{N}{\rho} \\ &\quad+\frac{\delta_k}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{w} \end{aligned}$$

$$
\begin{aligned}
&- \frac{1}{2\rho} \sum_{i=1}^{N} \left(\bar{\sigma}_i + \left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i \right) \bar{\sigma}_i^2 + \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i + \left(\delta_k - \bar{\delta}_i \right) \mathcal{G}_i \right)^2 \right) \left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}} \right) + \frac{N}{2\rho} \\
&+ \frac{\delta_j}{\rho} \mathbf{w}' \hat{\boldsymbol{\Sigma}}_k^{-1} \boldsymbol{\mathcal{G}} + \frac{\delta_j \delta_k}{\rho} \boldsymbol{\mathcal{G}}' \hat{\boldsymbol{\Sigma}}_k^{-1} \boldsymbol{\mathcal{G}} - c_j \left(\boldsymbol{S}_k \right) \\
= \; & rW_{0j} \\
&+ \frac{1}{\rho} \sum_{i=1}^{N} \left(\bar{\sigma}_i + \left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i \right) \bar{\sigma}_i^2 + \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i - \bar{\delta}_i \mathcal{G}_i \right)^2 \right) \left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}} \right) - \frac{N}{\rho} \\
&+ \sum_{i=1}^{N} \frac{\delta_j + \delta_k}{\rho} \mathcal{G}_i \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i - \bar{\delta}_i \mathcal{G}_i \right) \left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}} \right) \\
&- \frac{1}{2\rho} \sum_{i=1}^{N} \left(\bar{\sigma}_i + \left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i \right) \bar{\sigma}_i^2 + \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i + \left(\delta_k - \bar{\delta}_i \right) \mathcal{G}_i \right)^2 \right) \left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}} \right) + \frac{N}{2\rho} \\
&+ \frac{\delta_j \delta_k}{\rho} \sum_{i=1}^{N} \mathcal{G}_i^2 \left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}} \right) - \sum_{i=1}^{N} c_{ij} \left(S_{ik} \right).
\end{aligned}
\tag{A.66}
$$

The expected utility loss from following the suboptimal policy is equal to

$$
\begin{aligned}
U_{1j} - U_{1j|k} = \; & \frac{1}{\rho} \sum_{i=1}^{N} \left(\bar{\sigma}_i + \left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i \right) \bar{\sigma}_i^2 + \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i - \bar{\delta}_i \mathcal{G}_i \right)^2 \right) \left(S_{ij} - S_{ik} \right) \\
&+ \sum_{i=1}^{N} 2 \frac{\delta_j}{\rho} \mathcal{G}_i \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i - \bar{\delta}_i \mathcal{G}_i \right) \hat{\sigma}_{ij}^{-1} \\
&- \sum_{i=1}^{N} \frac{\delta_j + \delta_k}{\rho} \mathcal{G}_i \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i - \bar{\delta}_i \mathcal{G}_i \right) \hat{\sigma}_{ik}^{-1} \\
&+ \frac{1}{2\rho} \sum_{i=1}^{N} \left(\bar{\sigma}_i + \left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i \right) \bar{\sigma}_i^2 + \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i + \left(\delta_k - \bar{\delta}_i \right) \mathcal{G}_i \right)^2 \right) \hat{\sigma}_{ik}^{-1} \\
&- \frac{1}{2\rho} \sum_{i=1}^{N} \left(\bar{\sigma}_i + \left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i \right) \bar{\sigma}_i^2 + \left(\rho \bar{\mathcal{X}}_i \bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i \right) \mathcal{G}_i \right)^2 \right) \hat{\sigma}_{ij}^{-1} \\
&+ \frac{\delta_j^2}{\rho} \sum_{i=1}^{N} \mathcal{G}_i^2 \hat{\sigma}_{ij}^{-1} - \frac{\delta_j \delta_k}{\rho} \sum_{i=1}^{N} \mathcal{G}_i^2 \hat{\sigma}_{ik}^{-1} \\
&- \sum_{i=1}^{N} \left(c_{ij} \left(S_{ij} \right) - c_{ij} \left(S_{ik} \right) \right).
\end{aligned}
\tag{A.67}
$$

A.7 Portfolio dispersion and tracking error

The average dispersion of the portfolio positions in individual assets ($i = 1, ..., N-1$) per Proposition 5 is computed as

$$
\begin{aligned}
&\mathrm{E} \left[\sum_{i=1}^{N-1} \left(q_{ij} - \bar{q}_i \right)^2 \right] \\
&\quad = \mathrm{E} \left[\sum_{i=1}^{N-1} \left(\mathcal{Q}_{ij} - \bar{\mathcal{Q}}_i \right)^2 \right] \\
&\quad = \mathrm{E} \left[\sum_{i=1}^{N-1} \left(\frac{1}{\rho} \left(S_{ij} - \bar{S}_i \right) \left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i + V_{ii}^{\frac{1}{2}} u_i \right) + \frac{1}{\rho} S_{ij} \varepsilon_{ij} + \frac{1}{\rho} \hat{\sigma}_{ij}^{-1} \left(\delta_{ij} - \bar{\delta}_i \right) \mathcal{G}_i \right)^2 \right]
\end{aligned}
$$

$$
\begin{aligned}
&= \mathrm{E}\left[\sum_{i=1}^{N-1}\left(\left(S_{ij}-\bar{S}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i+\frac{1}{\rho}\left(S_{ij}-\bar{S}_i\right)V_{ii}^{\frac{1}{2}}u_i+\frac{1}{\rho}S_{ij}\boldsymbol{\varepsilon}_{ij}+\frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\Delta\delta_{ij}\mathcal{G}_i\right)^2\right]\\
&= \sum_{i=1}^{N-1}\left(\left(\left(S_{ij}-\bar{S}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i+\frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\Delta\delta_{ij}\mathcal{G}_i\right)^2+\frac{1}{\rho^2}\left(S_{ij}-\bar{S}_i\right)^2V_{ii}+\frac{1}{\rho^2}S_{ij}\right)\\
&= \sum_{i=1}^{N-1}\left(\left(\left(S_{ij}-\bar{S}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i+\frac{1}{\rho}\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\Delta\delta_{ij}\mathcal{G}_i\right)^2+\frac{1}{\rho^2}\left(S_{ij}-\bar{S}_i\right)^2V_{ii}+\frac{1}{\rho^2}S_{ij}\right)\\
&= \frac{1}{\rho^2}\sum_{i=1}^{N-1}\left(\left(S_{ij}\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\Delta\delta_{ij}\mathcal{G}_i\right)-\bar{S}_i\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\left(\sigma_i^{-1}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\Delta\delta_{ij}\mathcal{G}_i\right)^2+\left(S_{ij}-\bar{S}_i\right)^2V_{ii}+S_{ij}\right).
\end{aligned}
\tag{A.68}
$$

The return spread relative to the average portfolio is

$$
\begin{aligned}
&\left(\boldsymbol{q}_j-\bar{\boldsymbol{q}}\right)'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\\
&\quad=\left(\boldsymbol{\mathcal{Q}}_j-\bar{\boldsymbol{\mathcal{Q}}}\right)'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\\
&\quad=\frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1}-\bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right)+\mathbf{S}_j\boldsymbol{\varepsilon}_j+\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\left(\mathbf{w}+\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right).
\end{aligned}
\tag{A.69}
$$

The tracking error of the optimal portfolio relative to the market portfolio is then

$$
\begin{aligned}
\mathrm{TE}_j &= \mathrm{Var}\left[\left(\boldsymbol{q}_j-\bar{\boldsymbol{q}}\right)'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]=\mathrm{Var}\left[\left(\boldsymbol{\mathcal{Q}}_j-\bar{\boldsymbol{\mathcal{Q}}}\right)'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\\
&= \mathrm{Var}\left[\frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1}-\bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right)+\mathbf{S}_j\boldsymbol{\varepsilon}_j+\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\left(\mathbf{w}+\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right)\right]\\
&= \frac{1}{\rho^2}\mathrm{Var}\left[\left(\Delta\mathbf{S}_j\mathbf{V}^{\frac{1}{2}}\mathbf{u}+\mathbf{S}_j\boldsymbol{\varepsilon}_j\right)'\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right)+\left(\Delta\mathbf{S}_j\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right]\\
&= \frac{1}{\rho^2}\mathrm{Var}\left[\rho\boldsymbol{\varepsilon}_j'\mathbf{S}_j\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\mathbf{u}'\mathbf{V}^{\frac{1}{2}}\Delta\mathbf{S}_j\mathbf{V}^{\frac{1}{2}}\mathbf{u}+\boldsymbol{\varepsilon}_j'\mathbf{S}_j\mathbf{V}^{\frac{1}{2}}\mathbf{u}+\left(2\rho\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\Delta\mathbf{S}_j+\boldsymbol{\mathcal{G}}'\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\hat{\boldsymbol{\Sigma}}_j^{-1}\right)\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right]\\
&= \frac{1}{\rho^2}\sum_{i=1}^{N}\left[\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\right)^2S_{ij}+2\left(\Delta S_{ij}V_{ii}\right)^2+V_{ii}S_{ij}+\left(2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\Delta S_{ij}+\mathcal{G}_i\left(\delta_j-\bar{\delta}_i\right)\hat{\sigma}_{ij}^{-1}\right)^2V_{ii}\right].
\end{aligned}
\tag{A.70}
$$

In the last equality, the second term follows from $\mathrm{Var}\left[u_i^2\right]=2$, while the third term follows from the independence of ε_{ij} and u_i, which implies $\mathrm{Var}\left[\varepsilon_{ij}u_i\right]=\mathrm{Var}\left[\varepsilon_{ij}\right]\mathrm{Var}\left[u_i\right]=S_{ij}^{-1}$.

A.8 Sensitivity of the optimal signal precision to ESG preferences

We differentiate ψ_{ij} in Equation (A.45) with respect to $\left|\delta_j-\bar{\delta}\right|$

$$
\frac{\partial\psi_{ij}}{\partial\left|\delta_j-\bar{\delta}\right|}=\frac{\partial}{\partial\delta_j}\frac{\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\operatorname{sign}\left(\delta_j-\bar{\delta}_i\right)\cdot\left|\delta_j-\bar{\delta}_i\right|\mathcal{G}_i\right)^2}{2\rho}=\frac{\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i}{\rho}\cdot\operatorname{sign}\left(\delta_j-\bar{\delta}_i\right)\cdot\mathcal{G}_i.
\tag{A.71}
$$

When $c_{ij}(s)=\kappa s^2$ with $\kappa>0$, the optimal signal precision is strictly positive and equal to $S_{ij}=\frac{\psi_{ij}}{2\kappa}$. Then

$$
\frac{\partial S_{ij}}{\partial\left|\delta_j-\bar{\delta}\right|}=\frac{\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i}{2\kappa\rho}\cdot\operatorname{sign}\left(\delta_j-\bar{\delta}_i\right)\cdot\mathcal{G}_i.
\tag{A.72}
$$

Finally, we average across assets:

$$\frac{\partial \hat{S}_j}{\partial \left|\delta_j - \bar{\delta}\right|} = \frac{\partial}{\partial \left|\delta_j - \bar{\delta}\right|} \frac{\sum_{i=1}^{N} S_{ij}}{N} = \frac{1}{N} \sum_{i=1}^{N} \frac{\partial S_{ij}}{\partial \left|\delta_j - \bar{\delta}\right|} = \frac{1}{N} \sum_{i=1}^{N} \frac{\rho \bar{\sigma} + \left(\delta_j - \bar{\delta}\right) g_i}{2\kappa\rho} \cdot \operatorname{sign}\left(\delta_j - \bar{\delta}\right) \cdot g_i$$
$$= \operatorname{sign}\left(\delta_j - \bar{\delta}\right) \cdot \left(\frac{1}{N} \sum_{i=1}^{N} \frac{\bar{\sigma}}{2\kappa\rho} \cdot g_i + \frac{1}{N} \sum_{i=1}^{N} \frac{\delta_j - \bar{\delta}}{2\kappa\rho} g_i^2 \right) = \frac{\sigma_g}{2\kappa\rho} \left|\delta_j - \bar{\delta}\right|. \tag{A.73}$$

A.9 Expected net payoff and alpha

The expected excess net payoff is

$$\begin{aligned}
\mathrm{EENP}_j &= \mathrm{E}\left[\left(\boldsymbol{q}_j - \bar{\boldsymbol{q}}\right)' \left(\boldsymbol{f} - \boldsymbol{p} r\right)\right] \\
&= \frac{1}{\rho} \mathrm{E}\left[\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}} \mathbf{u}\right) + \mathbf{S}_j \boldsymbol{\varepsilon}_j + \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right) \boldsymbol{\mathcal{G}}\right)' \left(\mathbf{w} + \mathbf{V}^{\frac{1}{2}} \mathbf{u}\right)\right] \\
&= \frac{1}{\rho} \left(\rho \bar{\boldsymbol{\mathcal{X}}}' \bar{\boldsymbol{\Sigma}} \left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \mathbf{w} + \boldsymbol{\mathcal{G}}' \left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right)' \hat{\boldsymbol{\Sigma}}_j^{-1} \mathbf{w} + \mathrm{E}\left[\mathbf{u}' \mathbf{V}^{\frac{1}{2}} \left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \mathbf{V}^{\frac{1}{2}} \mathbf{u}\right]\right) \\
&= \frac{1}{\rho} \left(\rho \bar{\boldsymbol{\mathcal{X}}}' \bar{\boldsymbol{\Sigma}} \left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}} \boldsymbol{\mathcal{G}}\right) + \boldsymbol{\mathcal{G}}' \left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right)' \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}} \boldsymbol{\mathcal{G}}\right) + \operatorname{tr}\left[\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \mathbf{V}\right]\right) \\
&= \rho \bar{\boldsymbol{\mathcal{X}}}' \bar{\boldsymbol{\Sigma}} \left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\mathcal{X}}}' \bar{\boldsymbol{\Sigma}} \left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \bar{\boldsymbol{\delta}} \boldsymbol{\mathcal{G}} \\
&\quad + \frac{1}{\rho} \boldsymbol{\mathcal{G}}' \left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right)' \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}} \boldsymbol{\mathcal{G}}\right) + \frac{1}{\rho} \operatorname{tr}\left[\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \mathbf{V}\right] \\
&= \sum_{i=1}^{N} \rho \bar{\sigma}_i \bar{\mathcal{X}}_i^2 \left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) - \bar{\mathcal{X}}_i \left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) \bar{\delta}_i \mathcal{G}_i + \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} \bar{\mathcal{X}}_i \left(\delta_j - \bar{\delta}_i\right) \mathcal{G}_i - \frac{1}{\rho} \hat{\sigma}_{ij}^{-1} \left(\delta_j - \bar{\delta}_i\right) \bar{\delta}_i \mathcal{G}_i^2 + \frac{1}{\rho} \left(\hat{\sigma}_{ij}^{-1} - \bar{\sigma}_i^{-1}\right) V_{ii} \\
&= \sum_{i=1}^{N} \rho \bar{\sigma}_i \bar{\mathcal{X}}_i^2 \left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) - \bar{\mathcal{X}}_i \left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) \bar{\delta}_i \mathcal{G}_i + \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} \bar{\mathcal{X}}_i \Delta\delta_{ij} \mathcal{G}_i - \frac{1}{\rho} \hat{\sigma}_{ij}^{-1} \left(\delta_j - \bar{\delta}_i\right) \bar{\delta}_i \mathcal{G}_i^2 + \frac{1}{\rho} \Delta S_{ij} V_{ii} \\
&= \sum_{i=1}^{N} \left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i - \bar{\delta}_i \mathcal{G}_i\right) \bar{\sigma}_i \bar{\mathcal{X}}_i \Delta S_{ij} + \left(1 + \frac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}}\right) \bar{\mathcal{X}}_i \Delta\delta_{ij} \mathcal{G}_i - \frac{1}{\rho} \left(\bar{\sigma}_i^{-1} + \Delta S_{ij}\right) \Delta\delta_{ij} \bar{\delta}_i \mathcal{G}_i^2 + \frac{1}{\rho} \Delta S_{ij} V_{ii} \\
&= \sum_{i=1}^{N} \left(\left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i - \bar{\delta}_i \mathcal{G}_i\right) \bar{\sigma}_i \bar{\mathcal{X}}_i + \frac{1}{\rho} V_{ii}\right) \Delta S_{ij} + \frac{1}{\rho} \left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i - \bar{\delta}_i \mathcal{G}_i\right) \left(\bar{\sigma}_i^{-1} + \Delta S_{ij}\right) \Delta\delta_{ij} \mathcal{G}_i.
\end{aligned} \tag{A.74}$$

Equation (14) is obtained accounting for Equations (9), (10), (17), and (18), and imposing $\bar{\mathcal{X}}_i = 1$:

$$\begin{aligned}
\mathrm{EENP}_j &= \sum_{i=1}^{N} \left(\begin{array}{l} \left(\rho \bar{\sigma}_i - \bar{\delta}_i g_i\right) \dfrac{\Delta\delta_{ij} g_i}{\rho \bar{\sigma}_i} \\ + \left(\left(\rho \bar{\sigma}_i - \bar{\delta}_i g_i\right) \left(1 + \dfrac{\Delta\delta_{ij} g_i}{\rho \bar{\sigma}_i}\right) + \dfrac{V_{ii}}{\rho \bar{\sigma}_i}\right) \dfrac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}} \end{array} \right) \\
&= \sum_{i=1}^{N-1} \left(\mathrm{E}\left[\mathcal{Q}_{ij} - \bar{\mathcal{Q}}_i\right] \underbrace{\left(\rho \left(\bar{\sigma}_i + b_i \bar{\sigma}_N\right) - \bar{\delta}_i g_i\right)}_{\mathrm{E}\left[\mathcal{F}_i - \mathcal{P}_i\right]} + \frac{V_{ii}}{\rho \bar{\sigma}_i} \frac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}} \right) + \left(\mathrm{E}\left[\mathcal{Q}_{Nj} - \bar{\mathcal{Q}}_N\right] \underbrace{\rho \bar{\sigma}_N}_{\mathrm{E}\left[\mathcal{F}_N - \mathcal{P}_N\right]} + \frac{V_{NN}}{\rho \bar{\sigma}_N} \frac{\Delta S_{Nj}}{\bar{\sigma}_N^{-1}} \right) \\
&= \sum_{i=1}^{N} \left(\mathrm{E}\left[\mathcal{Q}_{ij} - \bar{\mathcal{Q}}_i\right] \mathrm{E}\left[\mathcal{F}_i - \mathcal{P}_i\right] + \frac{V_{ii}}{\rho} \Delta S_{ij} \right).
\end{aligned} \tag{A.75}$$

For a given asset, a fund earns a positive (negative) contribution to the EENP on assets where the signal precision is higher (lower) than the cross-agent average $S_{ij} > \bar{S}_i$ ($S_{ij} < \bar{S}_i$).

To prove Equations (15) and (16), we assume that $g_{gr} = \bar{g}$, $g_{br} = -\bar{g}$, $\Delta S_{grP} = \Delta S_{brI} = \Delta S$, $\Delta S_{grI} = \Delta S_{brP} = -\Delta S$, $\bar{\sigma}_{gr} = \bar{\sigma}_{br} = \bar{\sigma}$, $V_{gr} = V_{br} = V$, $\bar{\mathcal{X}}_{gr} = \bar{\mathcal{X}}_{br} = 1$, and $\bar{\delta}_{gr} = \bar{\delta}_{br} = \bar{\delta} = \frac{\delta_P + \delta_I}{2}$. Then:

$$\mathrm{EENP}_P = -2\bar{\delta}\bar{g}\frac{\bar{\delta}\bar{g}}{\rho\bar{\sigma}} = -\frac{\delta_P^2\bar{g}^2}{2\rho\bar{\sigma}}, \tag{A.76}$$

$$\mathrm{EENP}_I = 2\bar{\delta}\bar{g}\frac{\bar{\delta}\bar{g}}{\rho\bar{\sigma}} + 4\bar{\delta}\bar{g}\frac{\Delta S}{\bar{\sigma}^{-1}} = \frac{\delta_P^2\bar{g}^2}{2\rho\bar{\sigma}} + 2\delta_P\bar{g}\frac{\Delta S}{\bar{\sigma}^{-1}}. \tag{A.77}$$

We then evaluate the expected net payoff of agent j's portfolio, $\mathrm{ENP}_j = \mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]$. As $\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r = \mathbf{w} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}$, where $\mathbf{w} = \rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}$ and $\mathbf{V}^{\frac{1}{2}}\mathbf{u} = \bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\mathbf{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}$, and given $\boldsymbol{\mathcal{Q}}_j$ in Equation (A.55), we can write

$$\begin{aligned}
\mathrm{ENP}_j &= \mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right] = \mathrm{E}\left[\boldsymbol{\mathcal{Q}}_j'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right] \\
&= \mathrm{E}\left[\begin{array}{l} \frac{1}{\rho}\left(\begin{array}{l} \rho\hat{\mathbf{\Sigma}}_j^{-1}\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \hat{\mathbf{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}} + \left(\mathbf{S}_j - \hat{\mathbf{\Sigma}}_j^{-1}\left(\mathbf{I} - \bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\right) + \frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\boldsymbol{z} \\ + \left(\rho\hat{\mathbf{\Sigma}}_j^{-1}\bar{\mathbf{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right) - \frac{1}{\rho}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} + \mathbf{S}_j\boldsymbol{\varepsilon}_j \end{array}\right)' \\ \left(\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} + \bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\mathbf{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right) \end{array}\right] \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\mathrm{E}\left[\begin{array}{l} \left(\begin{array}{l} \rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\bar{\mathcal{X}}_i + \hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i + \left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \bar{\sigma}_i\sigma_i^{-1}\right) + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)z_i \\ + \left(\rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i + S_{ij}\varepsilon_{ij} \end{array}\right) \\ \cdot\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i + \bar{\sigma}_i\sigma_i^{-1}z_i + \rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right) \end{array}\right] \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\left[\begin{array}{l} \left(\rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\bar{\mathcal{X}}_i + \hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i\right)\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i\right) + \left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \bar{\sigma}_i\sigma_i^{-1}\right) + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i \\ + \left(\rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i} \end{array}\right].
\end{aligned} \tag{A.78}$$

Our aim is to study the alpha of agent j's portfolio, expressing it as

$$\alpha_j = \mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right] - \underbrace{\frac{\mathrm{Cov}\left[\boldsymbol{q}_j'\left(\boldsymbol{f}-\boldsymbol{p}r\right), \bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]}{\mathrm{Var}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]}}_{\beta_j}\mathrm{E}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right], \tag{A.79}$$

where $\mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]$ is the expected net payoff of portfolio j given in Equation (A.78), while the quantities $\mathrm{E}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]$, $\mathrm{Var}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]$, and $\mathrm{Cov}\left[\boldsymbol{q}_j'\left(\boldsymbol{f}-\boldsymbol{p}r\right), \bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right]$ are given by:

$$\begin{aligned}
\mathrm{E}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right] &= \mathrm{E}\left[\bar{\boldsymbol{\mathcal{Q}}}'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right] \\
&= \mathrm{E}\left[\left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)'\left(\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} + \bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\mathbf{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right)\right] \\
&= \sum_{i=1}^{N}\mathrm{E}\left[\left(\bar{\mathcal{X}}_i + \mathcal{X}_i\right)\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i + \bar{\sigma}_i\sigma_i^{-1}z_i + \rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right)\right] \\
&= \sum_{i=1}^{N}\left(\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i\right) + \rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i}\right),
\end{aligned} \tag{A.80}$$

$$\begin{aligned}
\mathrm{Var}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right] &= \mathrm{Var}\left[\bar{\boldsymbol{\mathcal{Q}}}'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right] \\
&= \mathrm{Var}\left[\left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)'\left(\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} + \bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\mathbf{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right)\right] \\
&= \sum_{i=1}^{N}\mathrm{Var}\left[\left(\bar{\mathcal{X}}_i + \mathcal{X}_i\right)\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i + \bar{\sigma}_i\sigma_i^{-1}z_i + \rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right)\right]
\end{aligned}$$

$$= \sum_{i=1}^{N} \mathrm{Var}\left[\left(\bar{\sigma}_i \sigma_i^{-1} \bar{\mathcal{X}}_i z_i + \left(\rho \bar{\sigma}_i \left(2 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \bar{\mathcal{X}}_i - \bar{\delta}_i \mathcal{G}_i\right) \mathcal{X}_i + \bar{\sigma}_i \sigma_i^{-1} z_i \mathcal{X}_i + \rho \bar{\sigma}_i \left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i^2\right)\right]$$

$$= \sum_{i=1}^{N} \left(\bar{\sigma}_i^2 \bar{\mathcal{X}}_i^2 \sigma_i^{-1} + \left(\rho \bar{\sigma}_i \left(2 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \bar{\mathcal{X}}_i - \bar{\delta}_i \mathcal{G}_i\right)^2 \sigma_{\mathcal{X}i} + \bar{\sigma}_i^2 \sigma_i^{-1} \sigma_{\mathcal{X}i} + 2\rho^2 \bar{\sigma}_i^2 \left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right)^2 \sigma_{\mathcal{X}i}^2\right), \tag{A.81}$$

and

$$\mathrm{Cov}\left[\boldsymbol{q}_j'\left(\boldsymbol{f} - \boldsymbol{p}r\right), \bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right] = \mathrm{Cov}\left[\boldsymbol{\mathcal{Q}}_j'\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right), \bar{\boldsymbol{\mathcal{Q}}}'\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]$$

$$= \mathrm{Cov}\left[\begin{array}{l} \frac{1}{\rho}\left(\begin{array}{l} \rho \hat{\boldsymbol{\Sigma}}_j^{-1} \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right) \boldsymbol{\mathcal{G}} + \left(\mathbf{S}_j - \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I} - \bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1}\right) + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1} \bar{\mathbf{S}}\right) \boldsymbol{z} \\ + \left(\rho \hat{\boldsymbol{\Sigma}}_j^{-1} \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) - \frac{1}{\rho} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}} + \mathbf{S}_j \boldsymbol{\varepsilon}_j \end{array}\right)' \\ \left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}} \boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1} \boldsymbol{z} + \rho \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}}\right), \\ \left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)'\left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}} \boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1} \boldsymbol{z} + \rho \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}}\right) \end{array}\right]$$

$$= \frac{1}{\rho} \mathrm{Cov}\left[\begin{array}{c} \left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}} \boldsymbol{\mathcal{G}}\right)'\left(\left(\mathbf{S}_j - \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I} - \bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1}\right) + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1} \bar{\mathbf{S}}\right) \boldsymbol{z} + \left(\rho \hat{\boldsymbol{\Sigma}}_j^{-1} \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) - \frac{1}{\rho} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}}\right) \\ + \left(\bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1} \boldsymbol{z} + \rho \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}}\right)'\left(\begin{array}{l} \rho \hat{\boldsymbol{\Sigma}}_j^{-1} \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right) \boldsymbol{\mathcal{G}} \\ + \left(\mathbf{S}_j - \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I} - \bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1}\right) + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1} \bar{\mathbf{S}}\right) \boldsymbol{z} \\ + \left(\rho \hat{\boldsymbol{\Sigma}}_j^{-1} \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) - \frac{1}{\rho} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}} \end{array}\right), \\ \left(\rho \bar{\boldsymbol{\mathcal{X}}}' \bar{\boldsymbol{\Sigma}} - \boldsymbol{\mathcal{G}}' \bar{\boldsymbol{\delta}}\right) \boldsymbol{\mathcal{X}} + \boldsymbol{\mathcal{X}}' \bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1} \boldsymbol{z} + \rho \boldsymbol{\mathcal{X}}' \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}} + \bar{\boldsymbol{\mathcal{X}}}' \bar{\boldsymbol{\Sigma}} \boldsymbol{\Sigma}^{-1} \boldsymbol{z} + \rho \bar{\boldsymbol{\mathcal{X}}}' \bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2} \bar{\mathbf{S}} \boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) \boldsymbol{\mathcal{X}} \end{array}\right]$$

$$= \frac{1}{\rho} \sum_{i=1}^{N} \mathrm{Cov}\left[\begin{array}{l} \left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i - \bar{\delta}_i \mathcal{G}_i\right)\left(\left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right) + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}\right) z_i + \left(\rho \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i\right) \\ + \left(\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}} z_i + \rho \bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i\right)\left(\begin{array}{l} \rho \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} \bar{\mathcal{X}}_i + \hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right) \mathcal{G}_i \\ + \left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right) + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}\right) z_i \\ + \left(\rho \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i \end{array}\right), \\ \left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i\left(2 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) - \bar{\delta}_i \mathcal{G}_i\right) \mathcal{X}_i + \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}} \bar{\mathcal{X}}_i z_i + \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}} \mathcal{X}_i z_i + \rho \bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i^2 \end{array}\right]$$

$$= \frac{1}{\rho} \sum_{i=1}^{N} \mathrm{E}\left[\begin{array}{l} \left[\begin{array}{l} \left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i - \bar{\delta}_i \mathcal{G}_i\right)\left(\left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right) + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}\right) z_i + \left(\rho \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i\right) \\ + \left(\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}} z_i + \rho \bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i\right)\left(\begin{array}{l} \rho \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} \bar{\mathcal{X}}_i + \hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right) \mathcal{G}_i \\ + \left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right) + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}\right) z_i \\ + \left(\rho \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i \end{array}\right) \end{array}\right] \\ \cdot \left[\left(\rho \bar{\sigma}_i \bar{\mathcal{X}}_i\left(2 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) - \bar{\delta}_i \mathcal{G}_i\right) \mathcal{X}_i + \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}} \bar{\mathcal{X}}_i z_i + \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}} \mathcal{X}_i z_i + \rho \bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i^2\right] \end{array}\right]$$

$$- \frac{1}{\rho} \sum_{i=1}^{N} \mathrm{E}\left[\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right) + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}\right) z_i^2 + \rho \bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right)\left(\rho \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i^2\right]$$

$$\cdot \mathrm{E}\left[\rho \bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) \mathcal{X}_i^2\right]$$

$$
\begin{aligned}
&= \frac{1}{\rho}\sum_{i=1}^{N}\left[\begin{array}{l}
\left(w_i\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i\sigma_i \\
+\left(w_i\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right) \\
\cdot\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\bar{\delta}_i\mathcal{G}_i\right)\sigma_{\mathcal{X}i} \\
+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\left(\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right)^2 3\sigma_{\mathcal{X}i}^2 \\
+\left(2\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\sigma_i\sigma_{\mathcal{X}i}
\end{array}\right] \\
&\quad -\frac{1}{\rho}\sum_{i=1}^{N}\left(\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i}\right) \\
&\quad \cdot\left(\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i}\right) \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\left[\begin{array}{l}
\left(w_i\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\bar{\mathcal{X}}_i\bar{\sigma}_i \\
+\left(w_i\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right) \\
\cdot\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\bar{\delta}_i\mathcal{G}_i\right)\sigma_{\mathcal{X}i} \\
+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\left(\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right)^2 2\sigma_{\mathcal{X}i}^2 \\
+\left(\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\bar{\sigma}_i\sigma_{\mathcal{X}i}
\end{array}\right].
\end{aligned}
\tag{A.82}
$$

A.10 Total signal precision

We evaluate the average signal precision across all assets and agents when $c_{ij}(s) = \kappa s^2$ with $\kappa > 0$. We assume, without loss of generality, that $\frac{1}{N}\sum_{i=1}^{N} g_i = 0$. Recall that ESG scores are ordinal in nature. We further assume that $\bar{\sigma}_i = \bar{\sigma}$, $\bar{\delta}_i = \bar{\delta} = \int_j \delta_j \mathrm{d}j$, $\bar{X}_i = 1$. The optimal signal precision is then given by

$$
S_{ij} = \frac{\bar{\sigma} + \left(\rho^2\sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma} + \left(\delta_j - \bar{\delta}\right)g_i\right)^2}{4\kappa\rho}. \tag{A.83}
$$

The average signal precision across all assets and agents is equal to

$$
\begin{aligned}
\hat{\bar{S}} &= \frac{1}{N}\sum_{i=1}^{N}\left(\int_j S_{ij}\mathrm{d}j\right) \\
&= \frac{1}{N}\sum_{i=1}^{N}\int_j \frac{\bar{\sigma} + \left(\rho^2\sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma} + \left(\delta_j - \bar{\delta}\right)g_i\right)^2}{4\kappa\rho}\mathrm{d}j \\
&= \frac{1}{N}\sum_{i=1}^{N}\int_j \frac{\bar{\sigma} + \left(\rho^2\sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma}\right)^2 + 2\rho\bar{\sigma}\left(\delta_j - \bar{\delta}\right)g_i + \left(\delta_j - \bar{\delta}\right)^2 g_i^2}{4\kappa\rho}\mathrm{d}j \\
&= \frac{\bar{\sigma} + \left(\rho^2\sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma}\right)^2 + \sigma_\delta\sigma_g}{4\kappa\rho},
\end{aligned}
\tag{A.84}
$$

where $\sigma_\delta = \int_j \left(\delta_j - \bar{\delta}\right)^2 \mathrm{d}j$ and $\sigma_g = \frac{1}{N}\sum_{i=1}^{N} g_i^2$. The last term in the numerator of Equation (A.84) is the only component that is explicitly originating from ESG considerations, leading to an incremental average signal precision equal to $\hat{\bar{S}}_{ESG} = \frac{\sigma_\delta\sigma_g}{4\kappa\rho}$.

B Calibration

We calibrate the model to assess its quantitative implications. The calibration considers an economy with two types of active funds: ESG indifferent ($\delta_I = 0$) and ESG perceptive ($\delta_P > 0$). The latter funds attribute value to holding green assets and they represent a fraction φ of the total mass of agents. Each individual fund is assumed to be atomistic, having no independent impact on equilibrium. There are three types of investable assets, namely, a green asset, a brown asset, and the ESG-neutral aggregate asset.

Without loss of generality, we assume the expected monetary payoff of all tradable assets to be equal to one dollar ($\mu_{gr} = \mu_{br} = \mu_{agg} = 1$). The prior variance of the aggregate asset payoff is set to $\sigma_{agg} = 0.15^2$. Hence, the volatility of the aggregate asset is 15% of the expected payoff, approximately matching the annualized historical volatility of the U.S. equity market (15.35% during the extended sample period from July 1963 through December 2021). The observed annual equity premium during that period is 7.07%. Based on Equation (17), if the posterior variance $\bar{\sigma}_{agg}$ were equal to the prior variance σ_{agg}, the expected net payoff $\rho\bar{\sigma}_{agg}$ would be equal to 6.75% for $\rho = 3$. We retain the value of three for the risk aversion parameter, which translates to a market premium slightly below 6.75%, as information acquisition leads to higher posterior precision.

We assume the green and brown assets have a unit loading on the aggregate risk factor ($b_{gr} = b_{br} = 1$), and the asset-specific shocks have variance given by $\sigma_{gr} = \sigma_{br} = 0.15^2$. Hence, the total variance of the individual asset payoff is approximately equal to 0.21^2. We further assume that the mean supply of all the risk factors is one unit and the standard deviation of the supply is 10% of the mean, namely $\sigma_{\mathcal{X}} = 0.1^2$.

We next set the ESG preference parameter, δ_P, as well as the individual asset ESG scores, g_{gr} and g_{br}. The expression $\delta_P g_{gr}$ ($\delta_P g_{br}$) represents the nonpecuniary effects from holding the green (brown) asset. We choose $\delta_P = 1$ as the benchmark value for ESG preferences and consider $g_{gr} = 0.05$ and $g_{br} = -0.05$. With these parameter specifications, sustainable funds perceive 5% of the expected financial payoff as nonpecuniary benefit (loss) due to holding one unit of the green (brown) asset. Thus, the green and brown assets considered here can be perceived as members in the cross-section of individual stocks that considerably depart from green neutrality.

The cost function is formulated as $c_{ij} = \kappa S_{ij}^2$. As the fund-level cost of information acquisition is the sum of c_{ij} across stock holdings, the value κ determines the information cost and, hence, the amount of information purchased in equilibrium. In our sample, active and index funds display an average expense ratio of 1.18% and 0.56%, respectively. The difference in fees, i.e., 0.62%, could establish a plausible proxy for the information acquisition cost. Thus, we choose $\kappa = 0.01$, which implies that informed funds optimally spend between 50 and 60 basis points to purchase information.

Equilibrium information decisions are determined as the solution to a fixed-point problem, where the signal precision in Equation (6) depends on the marginal benefit of information acquisition in Equation (7). This, in turn, relies on the aggregate signal precision through $\bar{S}_i$, $\bar{\sigma}_i$, and $\bar{\delta}_i$. In the calibration, the equilibrium is determined by numerically solving Equation (6) simultaneously for both ESG-perceptive and ESG-indifferent funds.

B.1 Understanding the individual fund

We analyze the optimal information acquisition policy and the portfolio characteristics for the marginal, individual, fund assuming $\varphi = 0.5$ and that the ESG preference parameter ranges between 0 and 1. Figure A.1 illustrates the calibration results, consisting of nine graphs.

Graph (a) shows the fund's optimal signal precision. Based on Equations (6) and (7), the signal precision increases (decreases) in δ_j for the green (brown) risk factors. When ESG preferences are near 0.5, the average value in the economy, the risk factors have identical signal precision.

Graph (b) shows the total cost of information acquisition, which is convex in ESG preferences, increasing for values of δ_j that deviate from 0.5. The calibration result indicates that the optimal cost of information acquisition is approximately 55 basis points, compatible with the observed gap between active and passive mutual fund expense ratios, as noted earlier.

Graph (c) shows the expected portfolio positions relative to the average position across agents. When ESG preferences are near 0.5, the expected portfolio positions are equal to the market portfolio. When $\delta_j = 1$, the expected position is approximately 0.4 units higher for the green asset and 0.4 units lower for the brown asset. Conversely, the brown asset dominates stock holdings when $\delta_j = 0$.

Graph (d) depicts the expected nonpecuniary payoff from ESG investing, i.e., $\mathrm{E}\left[\delta_j G_j\right]$. The expected nonpecuniary benefits are slightly negative when δ_j is below the average value in the economy, as the fund benefits from a more favorable financial profile of the assets it holds. The nonpecuniary benefits become positive when δ_j is greater than 0.5, reaching a maximum perceived value of 4% for $\delta_j = 1$.

Graph (e) displays the portfolio dispersion. The measure increases significantly when the fund ESG preference departs from the aggregate ESG preference, as described in Proposition 5. The portfolio dispersion is 0.095 for $\delta_j = 0.5$ and increases to 0.406 for δ_j that is equal to 0 or 1. Likewise, the tracking error, shown in Graph (f), substantially increases with the departure of the ESG preference from the average, ranging between 0.033 and 0.093.

Proposition 6 implies that the expected net payoff diminishes with the fund's ESG preferences. Per the calibration results, the portfolio expected net payoff, reported in Graph (g), is approximately 0.2, decreasing by approximately 0.04 for a unit increase in δ_j. In Online Appendix A.5, we also derive the CAPM alpha of the portfolio, displayed in Graph (h). Similar to the expected net payoff, the CAPM alpha decreases by approximately 4% when δ_j increases from 0 to 1, turning from positive to negative, due to increasingly overweighting green assets.

Finally, we assess the welfare implications of ESG motives. Following the derivations in Online Appendix A.6, Graph (i) displays the expected certainty equivalent loss perceived by a fund with ESG preference δ_j that is enforced to adopt the information decisions and portfolio strategy that are optimal for a fund with ESG preference δ_{sub}. We experiment with three values for δ_{sub}: 0, 0.5, and 1. The loss is expressed as a percentage of the optimal expected net payoff. The utility loss can be substantial when the distance between δ_j and δ_{sub} grows. For instance, an ESG-perceptive fund with $\delta_j = 1$ that adopts the information acquisition and portfolio policies of a fund with $\delta_{\text{sub}} = 0$ perceives a certainty equivalent loss of approximately 21.5% of the expected net payoff.

B.2 Price informativeness and the scope of the active fund industry

We examine the general equilibrium implications for the cross-section of price informativeness and the overall size of the active fund industry. Given our calibration, where the green and brown assets have identical characteristics except for their opposite ESG profiles, we should expect to see symmetric effects on the average signal precision and price informativeness for both types of assets.

Graph (a) shows the average signal precision across funds as a function of δ_P when $\varphi = 0.5$. The corresponding graph in the bottom row displays the variation in the aggregate signal precision with the choice of φ when $\delta_P = 1$. When all funds are ESG indifferent ($\delta_P = 0$ or $\varphi = 0$), the average signal precision for the green and brown risk factors is 0.4275, which leads to a posterior variance equal to 0.146^2, lower than the prior value (0.15^2) by more than 5%.[1] The average signal precision for both green and brown assets grows with the dispersion in ESG preferences, with a higher δ_P, and with the heterogeneity across agents (maximum heterogeneity obtains for $\varphi = 0.5$). Notably, the signal precision grows by 8.7% (from 0.4275 to 0.4649) when δ_P increases from 0 to 2. Furthermore, when $\delta_P = 1$, the signal precision grows by 2.2% (from 0.4275 to 0.4368) for $\varphi = 0.5$ relative to the case where there is no heterogeneity in ESG preferences ($\varphi = 0$ or 1).

Graph (b) in Figure A.2 shows the variation of price informativeness measure, $\mathrm{PI}_i = \frac{\mathrm{Cov}[f_i, p_i]}{\mathrm{Std}[p_i]}$, with δ_P. The price informativeness grows with δ_P for both the green and brown assets, increasing from 4.43 for $\delta_P = 0$, to 4.48 for $\delta_P = 1$, and to 4.62 for $\delta_P = 2$. The increase reflects the higher average signal precision shown in Graph (a). As the bottom

[1] According to Proposition 1, the posterior precision is directly increased by the signal precision, as well as indirectly through the price signal precision, i.e., $\bar{\sigma}_{gr}^{-1} = \sigma_{gr}^{-1} + \bar{S}_{gr} + \frac{\bar{S}_{gr}^2}{\rho^2 \sigma_{\mathcal{X}}} = \frac{1}{0.15^2} + 0.4275 + \frac{0.4275^2}{3^2 \times 0.1^2} \approx \frac{1}{0.146^2}$.

graph shows, the presence of ESG-perceptive funds implies an increase in price informativeness only when there is heterogeneity in ESG preferences. Price informativeness records the minimum value (4.43) when ESG motives are absent or homogeneous.

The analysis in Section 2.2 indicates that the active asset management industry's size may be significantly impacted by ESG motives, as evidenced by the sensitivity of information decisions to dispersions in cross-stock ESG attributes and cross-fund ESG preferences. In the calibration framework developed above, we use the aggregate cost of information acquisition as a proxy for the size of the active fund industry. The overall cost is given by $\varphi \cdot \sum_{i=1}^{N} \kappa S_{iP}^2 + (1-\varphi) \cdot \sum_{i=1}^{N} \kappa S_{iI}^2$, where S_{iP} and S_{iI} are the optimal signal precisions acquired by ESG-perceptive and ESG-indifferent agents for asset i, respectively. As shown in Graph (c) at the top, the total information cost grows with δ_P, from a minimum of 54.8 basis points for the case where all agents are ESG indifferent ($\delta_P = 0$), to 57.0 basis points for the base case value $\delta_P = 1$ (a 4% increase) and to 63.7 basis points for $\delta_P = 2$ (a 16% increase). The bottom graph confirms that the increase in information costs applies only when ESG preferences are dispersed, with the maximum dispersion corresponding to the case where $\varphi = 0.5$.

C Supplementary material

C.1 Cross-section of realized returns

To test the cross-sectional prediction using *realized* returns, we collect ESG rating data from additional data vendors, i.e., MSCI KLD and Sustainalytics, and extend the sample period to 2001. We divide the full sample into two subperiods, January 2001–October 2012 and November 2012–December 2021. We expect the results to be stronger in the first subperiod, which provides a cleaner setting to analyze the equilibrium asset pricing implications.[2]

We start with the firm-level ESG rating from each data provider. For the MSCI KLD data, we construct an aggregate ESG rating by summing all strengths and subtracting all concerns (e.g., Lins et al., 2017). Since the MSCI KLD data end in 2016, we complement them with the "ESG Rating" from MSCI ESG Ratings and "Total_ESG_Score" from Sustainalytics.[3] ESG rating agencies can differ in terms of their rating scale, e.g., MSCI KLD rating ranges from −11 to +19 in our sample, MSCI ESG Ratings uses a seven-tier rating scale from the best (AAA) to the worst (CCC), and Sustainalytics applies a scale from 0 to 100. To achieve comparability across the rating agencies, we proceed as follows. For each rater-month, we sort all stocks according to the original rating scale of the respective data provider and calculate the percentile rank (normalized between −0.5 and 0.5) for each stock-rater. Then, for each stock, we compute the average rank across all raters to obtain the firm-level ESG rating.[4] Finally, we define the fund-level ESG rating as the investment value-weighted average of stock-level ESG rating in a fund's most recently reported holding portfolio.

We repeat the analyses in Table 5 while replacing ICC with realized return during the holding period. Using the average rank also allows us to examine a larger number of firms, therefore, we sort stocks into 5×5 portfolios first by their green/brown fund ownership and then by ESG ratings. Online Appendix Table A.5 reports the results,

[2] The sample begins in 2001 when MSCI KLD expanded coverage to Russell 1000 firms (Nofsinger et al., 2019) and institutional investors display a growing preference for ESG investing during that period (Starks et al., 2023). We split the sample in October 2012 because Pástor et al. (2022) document that U.S. green stocks outperformed brown stocks from November 2012 to December 2020.

[3] Our MSCI KLD, MSCI ESG Ratings, and Sustainalytics samples extend from 2001 to 2016, 2006 to 2021, and 2009 to 2020, respectively. Each data vendor covers an average of 2,242, 1,544, and 1,283 firms per month, respectively, during the sample period.

[4] Using the average rank allows us to examine a longer sample period and a larger number of firms. It also mitigates the concern that our results could be driven by the idiosyncrasies in a specific ESG rating, given the rating disagreement across different ESG data vendors (e.g., Avramov et al., 2022). In addition, investors may rely on ESG ratings from different data vendors; therefore, the average rating provides an approximate assessment of the perceived ESG profile among investors.

with Panel A for raw return and CAPM-adjusted return and Panel B for FF6-adjusted return and DGTW-adjusted return. First, the negative ESG-return relation only holds among stocks with high green fund ownership during the first subperiod (Panels A1 and B1). Specifically, green stocks underperform brown stocks by 0.638% per month in raw return and 0.588% (0.630%, 0.489%) per month in CAPM-adjusted (FF6-adjusted, DGTW-adjusted) return. In contrast, the long-short portfolio ("HML-R") returns as well as the associated risk-adjusted and characteristic-adjusted returns are insignificant for the remaining firms. Notably, the negative ESG-return relation is concentrated in stocks with high green fund ownership because green stocks underperform more in the presence of information acquisition. The high-ESG, high-Green-IO stocks generate a significant CAPM alpha of −0.304% per month, while high-ESG stocks in other Green-IO quintiles deliver higher payoff.

Second, we find a significantly negative ESG-return relation among stocks with low brown fund ownership during the first subperiod (Panels A3 and B3). For instance, green stocks underperform brown stocks by 0.558% per month in raw return and 0.579% (0.586%, 0.540%) per month in CAPM-adjusted (FF6-adjusted, DGTW-adjusted) return. Importantly, the long-short portfolios ("HML-R") deliver less negative or insignificant payoff for the remaining firms. Furthermore, the negative return predictability of ESG ratings can be attributed to the outperformance of brown stocks. The low-ESG, low-Brown-IO stocks generate a significant CAPM alpha of 0.455% per month, while low-ESG stocks in other Brown-IO quintiles deliver a lower payoff.

Finally, moving to the more recent subperiod, green stocks outperform brown stocks especially among stocks with high green fund ownership (Panel A2). While our model does not capture the unexpected shift in investors' ESG preferences during this period, green stocks heavily invested in by green funds could be most exposed to this shift in preferences, therefore experiencing more price appreciation and higher realized returns. Indeed, high-ESG, high-Green-IO stocks yield a significantly positive CAPM alpha of 0.421% per month during the second subperiod.

For completeness, we report the results of ICC in the extended sample period. Online Appendix Table A.6 has a layout similar to Online Appendix Table A.5. Without loss of generality, we focus on ICC and DGTW-adjusted ICC when discussing the findings. First, green stocks exhibit lower ICC (DGTW-adjusted ICC) than brown stocks in both subperiods, and the monthly difference in a univariate sort is 0.103% (0.074%) in the first subperiod (Panels A1 and B1) and 0.054% (0.021%) in the second subperiod (Panels A2 and B2).

Second, the negative ESG-ICC relation is more pronounced among stocks with high green fund ownership (Panels A1, A2, B1, and B2). When green fund ownership is high, green stocks display 0.147% (0.104%) and 0.080% (0.034%) lower ICC (DGTW-adjusted ICC) per month than brown stocks in the first and second subperiod, respectively. The monthly difference in ICC (DGTW-adjusted ICC) spread between high- and low-green-fund-ownership portfolios is significant at −0.122% (−0.070%) in the first subperiod and −0.070% (−0.041%) in the second subperiod.

Finally, the negative ESG-ICC relation is also stronger among stocks with low brown fund ownership (Panels A3, A4, B3, and B4). When brown fund ownership is low, green stocks display 0.062% (0.068%) and 0.094% (0.052%) lower ICC (DGTW-adjusted ICC) per month than brown stocks in the first and second subperiod, respectively. The monthly difference in ICC (DGTW-adjusted ICC) spread between high- and low-brown-fund-ownership portfolios is significant at 0.049% (0.044%) in the first subperiod and 0.097% (0.066%) in the second subperiod.

Table A.1: Variables Definitions

Variables	Definitions
A. ESG Rating Measures	
Stock ESG	In each month, we sort all stocks according to the MSCI "Final Industry-Adjusted Company Score" (INDUSTRY_ADJUSTED_SCORE) and calculate the percentile rank (normalized between −0.5 and 0.5) for each stock.
Stock ESGDev	The stock-level departure from green neutrality of stock i in a given month t is computed as follows: $\text{ESGDev}_{i,t} = \lvert\text{Stock ESG}_{i,t}\rvert$, where Stock $\text{ESG}_{i,t}$ is the ESG rating of stock i in month t, which is defined as in the *Stock ESG* above.
Stock Residual ESG	In each month, we run a least absolute shrinkage and selection operator (LASSO) regression of stock ESG scores on 94 industry-adjusted and normalized stock characteristics and obtain the estimated residuals. Stock ESG scores are obtained from MSCI "Final Industry-Adjusted Company Score" (INDUSTRY_ADJUSTED_SCORE), and details on each of the 94 firm characteristics can be found in the Appendix in Green et al. (2017) and Internet Appendix Table A.6 in Gu et al. (2020). We rank all stock characteristics within each industry-month and normalize these ranks between 0 and 1. We do not perform such industry adjustment for dummy variables. The ranks for missing characteristics are set to be 0.5 (industry median).
Fund ESG Preference	The investment value-weighted average of the stock residual ESG rating in a fund's most recently reported holding portfolio (normalized between 0 and 1). The stock residual ESG rating is defined as in the *Stock Residual ESG* above.
Stock ESGDisp	The heterogeneity in the ESG preferences of stock i in a given month t is the (investment value-weighted) standard deviation of the fund ESG preference of all funds that hold stock i in month t. The fund ESG preference is defined as in the *Fund ESG Preference* above.
Fund ESGDev	The departure of fund j's ESG preference from the aggregate in a given month t is computed as follows: Fund $\text{ESGDev}_{j,t} = \lvert\text{Fund ESG Preference}_{j,t} - 0.5\rvert$, where Fund ESG $\text{Preference}_{j,t}$ is the ESG preference of fund j in month t, which is defined as in the *Fund ESG Preference* above.
B. Other Fund Characteristics	
HHI	The portfolio dispersion of fund j in a given month t is computed as follows: $\text{HHI}_{j,t} = \sum_{i=1}^{N_{j,t}} \left(w_{i,j,t} - w^b_{i,j,t}\right)^2$, where $w_{i,j,t}$ is the investment weight of stock i by fund j in month t, $w^b_{i,j,t}$ is the investment weight of stock i in fund j's benchmark portfolio at the same time, and $N_{j,t}$ is the total number of stocks in the universe of fund j's holding portfolio and benchmark portfolio at the same time. We define the benchmark of the mutual funds based on the Primary Prospectus Benchmark from the Morningstar mutual fund database.
TE	The tracking error of fund j in a given month t, $\text{TE}_{j,t}$, is obtained from the following daily regression with a 6-month estimation period (month $t-5$ to month t): $R_{j,d} = \alpha + \beta R^b_{j,d} + \epsilon_{j,d}$, where $R_{j,d}$ is the excess return of fund j on day d, and $R^b_{j,d}$ is the excess return on fund j's benchmark index at the same time. $\text{TE}_{j,t}$ is the variance of $\epsilon_{j,d}$, following Cremers and Petajisto (2009). We define the benchmark of the mutual funds based on the Primary Prospectus Benchmark from the Morningstar mutual fund database.
Fund Return	The monthly net-of-fee return reported by the CRSP survivorship bias-free mutual fund database. When a fund has multiple share classes, its total return is computed as the share class total net assets (TNA)-weighted return of all share classes, where the TNA values are lagged by one month.
Fund Flow	The flow of fund j in a given month t is computed as follows: $\text{Flow}_{j,t} = \frac{\text{TNA}_{j,t} - \text{TNA}_{j,t-1} \times (1+r_{j,t})}{\text{TNA}_{j,t-1}}$, where $\text{TNA}_{j,t}$ is the TNA of fund j in month t, and $r_{j,t}$ is the fund return at the same time.
Log(Fund TNA)	The logarithm of the total net assets, as reported in the CRSP survivorship bias-free mutual fund database.
Expense Ratio	The annualized expense ratio, as reported in the CRSP survivorship bias-free mutual fund database.
Fund Turnover	The annualized turnover ratio, as reported in the CRSP survivorship bias-free mutual fund database.
Log(Fund Age)	The logarithm of the number of operational months since inception.
Flow Volatility	The standard deviation of the monthly fund flows in the previous 12 months.

Table A.1 (continued)

Variables	Definitions
C. Other Stock Characteristics	
E/A	The earnings before interest and taxes (COMPUSTAT annual item EBIT) divided by the total assets (item AT).
Log(M/A)	The logarithm of the market capitalization-to-total assets ratio, where market capitalization is defined as in *Log(Size)*, and total assets is reported in COMPUSTAT (annual item AT).
IO	The number of shares held by institutions divided by the number of shares outstanding.
Log(Asset)	The logarithm of the total assets (COMPUSTAT annual item AT).
Leverage	The total liabilities (COMPUSTAT annual item LT) divided by the total assets (item AT).
Tangibility	The net property, plant, and equipment (COMPUSTAT annual item PPENT) divided by the total assets (item AT).
Log(Sales)	The logarithm of the sales (COMPUSTAT annual item SALE).
Cash	The cash holdings (COMPUSTAT annual item CH) divided by the total assets (item AT).
Log(Analyst Coverage)	The logarithm of the number of analysts following a firm as reported in I/B/E/S.
Analyst Dispersion	The standard deviation of analysts' earnings (earnings per share, EPS) forecasts divided by the absolute value of the average earnings forecast as reported in I/B/E/S.
Green IO	The number of shares held by green funds divided by the number of shares outstanding. Green funds refer to funds with ESG preference in the top quintile across all funds. The fund ESG preference is defined as in the *Fund ESG Preference* above.
Brown IO	The number of shares held by brown funds divided by the number of shares outstanding. Brown funds refer to funds with ESG preference in the bottom quintile across all funds. The fund ESG preference is defined as in the *Fund ESG Preference* above.
IVOL	The standard deviation of the residuals estimated from the Fama-French-Carhart four-factor model (Fama and French, 1993; Carhart, 1997) by using the daily returns in a month. More specifically, we regress the daily stock excess return on the market, size, book-to-market, and momentum factor returns and obtain the residuals.
RETVOL	The standard deviation of the daily stock returns in a month.
Active IO	The number of shares held by U.S. actively managed equity mutual funds divided by the number of shares outstanding.
Log(Size)	The logarithm of the stock market capitalization, which is computed as the number of common shares outstanding times the share price as reported in CRSP.
Log(BM)	The logarithm of the book-to-market ratio, which is defined as the book value of equity divided by market capitalization at fiscal year-end. The book value of equity is computed as the stockholders' equity (COMPUSTAT annual item SEQ), plus deferred taxes and investment tax credit (item TXDITC), minus the book value of the preferred stock. Depending on availability, we use the redemption value (item PSTKRV), liquidation value (item PSTKL), or carrying value (item PSTK) to estimate the book value of the preferred stock, following Fama and French (1993) and Davis et al. (2000).
ROE	The return on equity of stock i in a given quarter q is computed as follows: $\text{ROE}_{i,q} = \text{INCOME}_{i,q}/\text{EQUITY}_{i,q-1}$, where $\text{INCOME}_{i,q}$ is the income before extraordinary items (COMPUSTAT quarterly item IBQ) of stock i in quarter q, and $\text{EQUITY}_{i,q-1}$ is the shareholders' equity. Depending on availability, we use stockholders' equity (item SEQQ), common equity (item CEQQ) plus redemption value (item PSTKRQ), common equity (item CEQQ) plus the carrying value of the preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in this order as shareholders' equity, following Hou et al. (2015).
I/A	The investment-to-assets of stock i in a given quarter q is computed as follows: $\text{I/A}_{i,q} = \text{AT}_{i,q}/\text{AT}_{i,q-4} - 1$, where $\text{AT}_{i,q}$ is the total assets (COMPUSTAT quarterly item ATQ) of stock i in quarter q.
1M Return	The monthly stock return.
12M Return	The past return in a given month t is computed as the cumulative 11-month return from month $t-11$ to month $t-1$, following Jegadeesh and Titman (1993).
CFO/A	The cash flows from operations divided by the total assets (COMPUSTAT annual item AT). The cash flows from operations (CFO) of stock i in a given year y is computed as follows: $\text{CFO}_{i,y} = \text{Earnings}_{i,y} - ((\text{CA}_{i,y} - \text{CA}_{i,y-1}) - (\text{CL}_{i,y} - \text{CL}_{i,y-1}) - (\text{CH}_{i,y} - \text{CH}_{i,y-1}) + (\text{STD}_{i,y} - \text{STD}_{i,y-1}) - (\text{D}_{i,y} - \text{D}_{i,y-1}))$, where $\text{Earnings}_{i,y}$ is the income before extraordinary items (item IB) of stock i in year y, $\text{CA}_{i,y}$ is the current assets (item ACT), $\text{CL}_{i,y}$ is the current liabilities (item LCT), $\text{CH}_{i,y}$ is the cash and short-term investments (item CHE), $\text{STD}_{i,y}$ is the debt included in current liabilities (item DLC), and $\text{D}_{i,y}$ is the depreciation and amortization expense (item DP), following Dechow et al. (1995).
FCF/A	The free cash flows divided by the total assets (COMPUSTAT annual item AT), where the free cash flows equals the cash flows from operations (defined as in the *CFO/A* above) minus the capital expenditures (item CAPX).

Table A.2: Stock Price Informativeness: Alternative Price Informativeness Measures (Robustness of Table 2)

Panel A presents the results of the following annual Fama-MacBeth regression and their corresponding Newey-West adjusted t-statistics:

$$\frac{CFO_{i,y+h}}{A_{i,y}} = \alpha + \beta_1 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) + \beta_2 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDev_{i,y} + \beta_3 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDisp_{i,y}$$
$$+ \beta_4 ESGDev_{i,y} + \beta_5 ESGDisp_{i,y} + \beta_6 \left(\frac{CFO_{i,y}}{A_{i,y}}\right) + cN_{i,y} + \varepsilon_{i,y+h},$$

where $CFO_{i,y+h}$ is the cash flows from operations of stock i in year $y+h$, $A_{i,y}$ is the total assets, $M_{i,y}$ is the market capitalization, $ESGDev_{i,y}$ is the departure from green neutrality, and $ESGDisp_{i,y}$ is the stock-level heterogeneity in the fund ESG preferences. Vector N stacks all other stock-level control variables, namely, the IO, Log(Asset), Leverage, Tangibility, Log(Sales), Cash, Log(Analyst Coverage), and Analyst Dispersion. Models 1-4, Models 5-8, and Models 9-12 report the results when $h = 1$, $h = 3$, and $h = 5$, respectively. Panel B reports similar statistics when cash flows from operations are replaced with free cash flows. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Stock Price Informativeness Based on Cash Flows from Operations

Dep. Var. =	$CFO_{i,y+1}/A_{i,y}$				$CFO_{i,y+3}/A_{i,y}$				$CFO_{i,y+5}/A_{i,y}$			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Log(M/A)	0.013***	0.005	-0.012*	-0.015*	0.015***	0.002	-0.033*	-0.036*	0.015*	-0.005	-0.034	-0.041*
	(3.89)	(0.95)	(-1.92)	(-1.95)	(3.53)	(0.21)	(-2.03)	(-2.03)	(2.18)	(-0.36)	(-1.77)	(-1.96)
Log(M/A) × Stock ESGDev		0.055***		0.039***		0.090***		0.059***		0.139***		0.096*
		(9.25)		(5.08)		(4.75)		(3.04)		(3.31)		(2.20)
Log(M/A) × Stock ESGDisp			0.156***	0.136***			0.282***	0.246***			0.290***	0.242***
			(8.18)	(7.86)			(3.55)	(3.29)			(3.88)	(4.53)
Stock ESGDev		0.000		-0.001		0.000		-0.004		-0.026		-0.031
		(0.02)		(-0.10)		(0.02)		(-0.42)		(-1.52)		(-1.61)
Stock ESGDisp			-0.022	-0.021			0.074**	0.075**			0.061	0.058
			(-0.81)	(-0.78)			(2.70)	(2.77)			(1.41)	(1.44)
CFO/A	0.587***	0.578***	0.576***	0.571***	0.625***	0.612***	0.608***	0.600***	0.673***	0.652***	0.650***	0.638***
	(14.86)	(14.94)	(14.74)	(14.78)	(9.73)	(9.92)	(9.85)	(10.01)	(7.72)	(7.95)	(7.83)	(7.96)
IO	0.019**	0.018**	0.020***	0.018***	0.008	0.007	0.008	0.007	-0.005	-0.002	-0.002	-0.001
	(2.58)	(2.69)	(3.13)	(3.18)	(0.67)	(0.67)	(0.73)	(0.63)	(-0.31)	(-0.14)	(-0.14)	(-0.05)
Log(Asset)	-0.012***	-0.012***	-0.012***	-0.012***	-0.018**	-0.018**	-0.019***	-0.019***	-0.022***	-0.022***	-0.023***	-0.022***
	(-5.27)	(-5.12)	(-5.59)	(-5.28)	(-2.92)	(-2.97)	(-3.35)	(-3.35)	(-4.69)	(-4.74)	(-4.62)	(-4.74)
Leverage	0.012	0.010	0.009	0.008	0.001	-0.001	-0.005	-0.006	-0.004	-0.010	-0.011	-0.015
	(1.52)	(1.38)	(1.12)	(1.09)	(0.05)	(-0.07)	(-0.28)	(-0.33)	(-0.19)	(-0.43)	(-0.53)	(-0.65)
Tangibility	0.003	0.002	-0.001	-0.001	-0.020	-0.022	-0.025	-0.027	-0.026	-0.031	-0.028	-0.032
	(0.27)	(0.14)	(-0.05)	(-0.10)	(-0.96)	(-1.07)	(-1.20)	(-1.25)	(-1.55)	(-1.65)	(-1.66)	(-1.69)
Log(Sales)	0.024***	0.025***	0.025***	0.025***	0.031***	0.032***	0.033***	0.033***	0.031***	0.034***	0.033***	0.035***
	(9.90)	(10.19)	(10.77)	(10.87)	(4.92)	(5.17)	(5.34)	(5.50)	(7.29)	(7.70)	(7.48)	(7.78)
Cash	-0.151***	-0.143***	-0.144***	-0.139***	-0.121***	-0.109***	-0.109***	-0.102***	-0.115***	-0.096***	-0.100***	-0.088***
	(-11.69)	(-11.76)	(-11.56)	(-11.59)	(-4.46)	(-4.39)	(-4.36)	(-4.35)	(-5.98)	(-4.72)	(-5.07)	(-4.17)
Log(Analyst Coverage)	-0.008***	-0.008**	-0.008***	-0.008***	-0.008	-0.008	-0.009*	-0.009*	0.009	0.008	0.007	0.007
	(-2.95)	(-2.83)	(-3.25)	(-3.13)	(-1.62)	(-1.62)	(-1.98)	(-1.96)	(1.49)	(1.49)	(1.30)	(1.30)
Analyst Dispersion	0.003	0.003	0.003	0.003	-0.001	-0.000	-0.001	0.000	0.004	0.006	0.004	0.006
	(0.54)	(0.64)	(0.53)	(0.61)	(-0.18)	(-0.03)	(-0.09)	(0.02)	(1.05)	(1.45)	(1.21)	(1.50)
Constant	-0.040***	-0.045***	-0.039***	-0.043***	-0.014	-0.021	-0.022	-0.027	0.009	-0.006	-0.002	-0.014
	(-3.43)	(-3.95)	(-4.26)	(-4.26)	(-0.81)	(-1.23)	(-1.26)	(-1.58)	(0.51)	(-0.39)	(-0.16)	(-1.00)
Obs	31,447	31,447	31,447	31,447	24,081	24,081	24,081	24,081	18,124	18,124	18,124	18,124
R-squared	0.510	0.513	0.515	0.517	0.364	0.369	0.372	0.375	0.269	0.276	0.277	0.281

Panel B: Stock Price Informativeness Based on Free Cash Flows

Dep. Var. =	$FCF_{i,y+1}/A_{i,y}$				$FCF_{i,y+3}/A_{i,y}$				$FCF_{i,y+5}/A_{i,y}$			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Log(M/A)	0.005**	-0.004	-0.024***	-0.027***	0.002	-0.013*	-0.050***	-0.054***	-0.002	-0.024*	-0.055**	-0.062**
	(2.57)	(-1.14)	(-4.93)	(-4.57)	(0.43)	(-1.79)	(-3.23)	(-3.24)	(-0.38)	(-1.85)	(-2.85)	(-2.94)
Log(M/A) × Stock ESGDev		0.065***		0.046***		0.102***		0.069***		0.145***		0.102**
		(12.10)		(6.45)		(6.42)		(4.12)		(4.11)		(2.85)
Log(M/A) × Stock ESGDisp			0.179***	0.155***			0.305***	0.264***			0.312***	0.256***
			(9.69)	(8.91)			(3.77)	(3.44)			(3.76)	(4.16)
Stock ESGDev		0.009		0.008		0.017**		0.013*		-0.009		-0.014
		(1.08)		(0.80)		(2.60)		(2.10)		(-0.55)		(-0.75)
Stock ESGDisp			-0.031	-0.030			0.064*	0.065**			0.042	0.039
			(-1.17)	(-1.15)			(2.09)	(2.21)			(1.27)	(1.22)
FCF/A	0.588***	0.578***	0.576***	0.570***	0.631***	0.617***	0.612***	0.604***	0.698***	0.676***	0.673***	0.660***
	(15.58)	(15.76)	(15.41)	(15.57)	(8.96)	(9.15)	(9.03)	(9.22)	(8.60)	(8.93)	(8.83)	(9.02)
IO	0.024***	0.024***	0.026***	0.025***	0.017	0.017	0.018	0.017	0.008	0.011	0.011	0.012
	(3.15)	(3.40)	(3.90)	(4.12)	(1.44)	(1.55)	(1.57)	(1.57)	(0.42)	(0.69)	(0.68)	(0.87)
Log(Asset)	-0.011***	-0.012***	-0.011***	-0.012***	-0.015***	-0.016***	-0.017***	-0.017***	-0.018***	-0.018***	-0.018***	-0.018***
	(-4.64)	(-4.80)	(-4.85)	(-4.95)	(-3.02)	(-3.16)	(-3.42)	(-3.53)	(-5.52)	(-5.55)	(-5.37)	(-5.53)
Leverage	0.012	0.011	0.009	0.008	-0.009	-0.011	-0.015	-0.016	-0.020	-0.025	-0.027	-0.030
	(1.56)	(1.42)	(1.10)	(1.08)	(-0.47)	(-0.58)	(-0.81)	(-0.85)	(-0.83)	(-1.04)	(-1.17)	(-1.27)
Tangibility	-0.032**	-0.034***	-0.037***	-0.038***	-0.060***	-0.064***	-0.068***	-0.070***	-0.079***	-0.086***	-0.085***	-0.089***
	(-2.85)	(-3.05)	(-3.27)	(-3.37)	(-3.30)	(-3.57)	(-3.85)	(-4.00)	(-4.43)	(-4.75)	(-4.94)	(-5.06)
Log(Sales)	0.024***	0.025***	0.025***	0.026***	0.031***	0.032***	0.033***	0.033***	0.034***	0.036***	0.036***	0.037***
	(11.60)	(11.79)	(12.88)	(12.77)	(5.91)	(6.06)	(6.45)	(6.49)	(9.11)	(9.55)	(9.21)	(9.58)
Cash	-0.096***	-0.087***	-0.087***	-0.081***	-0.057	-0.043	-0.041	-0.034	-0.018	0.004	0.002	0.015
	(-4.48)	(-4.23)	(-4.16)	(-4.04)	(-1.59)	(-1.32)	(-1.26)	(-1.11)	(-0.45)	(0.11)	(0.06)	(0.45)
Log(Analyst Coverage)	-0.014***	-0.014***	-0.015***	-0.015***	-0.015***	-0.015***	-0.016***	-0.016***	-0.004	-0.005	-0.005	-0.006
	(-7.34)	(-7.15)	(-8.15)	(-7.96)	(-4.18)	(-4.14)	(-4.74)	(-4.66)	(-0.78)	(-1.04)	(-1.08)	(-1.29)
Analyst Dispersion	-0.005	-0.005	-0.005	-0.005	-0.006	-0.005	-0.006	-0.005	-0.002	-0.001	-0.002	-0.001
	(-1.18)	(-1.10)	(-1.21)	(-1.15)	(-1.18)	(-0.98)	(-1.09)	(-0.94)	(-0.55)	(-0.23)	(-0.50)	(-0.20)
Constant	-0.049***	-0.052***	-0.049***	-0.050***	-0.035**	-0.039**	-0.044**	-0.045**	-0.036*	-0.048**	-0.048***	-0.056***
	(-4.53)	(-4.87)	(-5.96)	(-5.53)	(-2.43)	(-2.48)	(-2.81)	(-2.77)	(-2.16)	(-2.86)	(-3.42)	(-3.85)
Obs	31,422	31,422	31,422	31,422	24,056	24,056	24,056	24,056	18,106	18,106	18,106	18,106
R-squared	0.492	0.495	0.497	0.499	0.345	0.350	0.354	0.357	0.263	0.269	0.270	0.274

Table A.3: Implied Cost of Capital of Portfolios Sorted by Mutual Fund Ownership and ESG Rating: Composite ICC Measure (Robustness of Table 5)

In Panel A1, at the end of month t, stocks are first sorted into terciles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 15 (3×5) portfolios. The low- (high)-green-fund-ownership portfolios comprise the bottom (top) tercile of stocks based on the green fund ownership, and the low- (high)-ESG-rating portfolios comprise the bottom (top) quintile of stocks based on the ESG rating. For each of the 15 portfolios, we compute the value-weighted implied cost of capital (ICC) in month t+1 and rebalance the portfolios at the end of month t+1. We employ the composite of the mechanical-based ICCs for each stock-month following Lee et al. (2021), and report the time-series averages of the monthly ICCs for each of the 15 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for portfolios sorted only by green fund ownership. The portfolio ICCs are further adjusted by the CAPM. Panel A2 reports similar statistics when we replace green fund ownership with brown fund ownership. We identify green (brown) funds as those with a fund ESG preference in the top (bottom) quintile across all funds at the end of each month. Panel B reports similar statistics based on Fama-French six-factor-adjusted ICCs (FF6) and characteristic-adjusted ICCs per Daniel et al. (1997) (DGTW). The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Monthly Raw and CAPM-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings

	ICC							CAPM-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.267***	0.220***	0.228***	0.253***	0.223***	-0.044	0.242***	0.210***	0.158***	0.167***	0.191***	0.167***	-0.043	0.183***
	(5.53)	(7.74)	(6.96)	(7.07)	(5.06)	(-1.15)	(7.02)	(3.66)	(4.05)	(4.05)	(4.20)	(3.19)	(-1.03)	(4.16)
Mid	0.152***	0.157***	0.199***	0.145***	0.090**	-0.061**	0.151***	0.085*	0.096**	0.132***	0.081**	0.037	-0.049*	0.088**
	(3.93)	(5.43)	(5.99)	(5.88)	(2.01)	(-2.10)	(5.40)	(1.84)	(2.32)	(3.23)	(2.40)	(0.71)	(-1.66)	(2.35)
High	0.022	-0.020	-0.027	-0.066**	-0.117***	-0.139***	-0.054*	-0.041	-0.078**	-0.091**	-0.126***	-0.180***	-0.140***	-0.116***
	(0.74)	(-0.59)	(-0.87)	(-2.11)	(-3.96)	(-8.07)	(-1.89)	(-1.12)	(-2.04)	(-2.43)	(-3.52)	(-5.01)	(-8.11)	(-3.32)
HML-G	-0.245***	-0.240***	-0.255***	-0.319***	-0.340***	-0.095**	-0.296***	-0.250***	-0.235***	-0.258***	-0.317***	-0.347***	-0.097**	-0.299***
	(-4.79)	(-8.27)	(-9.64)	(-9.55)	(-11.94)	(-2.13)	(-11.53)	(-4.82)	(-7.77)	(-9.89)	(-9.28)	(-11.97)	(-2.09)	(-11.44)
All	0.102***	0.086***	0.077**	0.025	-0.086***	-0.187***		0.041	0.026	0.016	-0.037	-0.147***	-0.188***	
	(2.92)	(2.78)	(2.19)	(0.76)	(-2.68)	(-10.50)		(0.95)	(0.62)	(0.38)	(-0.94)	(-3.82)	(-9.94)	
Panel A2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.062	0.049	0.031	-0.037	-0.111***	-0.173***	-0.032	-0.001	-0.014	-0.032	-0.095**	-0.175***	-0.174***	-0.094**
	(1.53)	(1.14)	(0.95)	(-0.95)	(-3.46)	(-7.32)	(-0.99)	(-0.03)	(-0.30)	(-0.86)	(-2.20)	(-4.46)	(-7.92)	(-2.47)
Mid	0.168***	0.111***	0.114***	0.059**	-0.010	-0.178***	0.092***	0.108**	0.054	0.053	-0.002	-0.070*	-0.178***	0.032
	(3.93)	(2.61)	(3.19)	(2.05)	(-0.34)	(-6.63)	(2.88)	(1.98)	(1.04)	(1.32)	(-0.06)	(-1.88)	(-6.28)	(0.77)
High	0.084***	0.128***	0.120***	0.107***	0.067***	-0.017	0.098***	0.025	0.066*	0.059	0.046	0.005	-0.020	0.037
	(3.09)	(4.99)	(4.81)	(4.42)	(2.89)	(-0.88)	(4.45)	(0.69)	(1.96)	(1.64)	(1.30)	(0.15)	(-1.06)	(1.13)
HML-B	0.023	0.079**	0.089***	0.144***	0.179***	0.156***	0.131***	0.026	0.080**	0.091**	0.141***	0.180***	0.154***	0.131***
	(0.50)	(2.10)	(2.66)	(4.59)	(6.79)	(4.47)	(4.96)	(0.62)	(2.05)	(2.57)	(4.46)	(6.55)	(4.70)	(4.84)
All	0.102***	0.086***	0.077**	0.025	-0.086***	-0.187***		0.041	0.026	0.016	-0.037	-0.147***	-0.188***	
	(2.92)	(2.78)	(2.19)	(0.76)	(-2.68)	(-10.50)		(0.95)	(0.62)	(0.38)	(-0.94)	(-3.82)	(-9.94)	

Panel B: Monthly FF6- and DGTW-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings

	FF6-adjusted ICC							DGTW-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel B1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.199***	0.153***	0.161***	0.192***	0.163***	-0.036	0.176***	0.070**	0.030**	0.030**	0.049***	0.031*	-0.039	0.048***
	(3.66)	(4.12)	(4.16)	(4.51)	(3.40)	(-0.95)	(4.30)	(2.54)	(2.31)	(2.47)	(2.73)	(1.65)	(-1.43)	(3.75)
Mid	0.083**	0.092**	0.130***	0.081**	0.034	-0.049*	0.087***	0.034*	0.061***	0.094***	0.079***	-0.004	-0.038**	0.059***
	(2.17)	(2.40)	(3.32)	(2.55)	(0.78)	(-1.69)	(2.61)	(1.91)	(2.99)	(4.34)	(5.53)	(-0.27)	(-2.36)	(4.87)
High	-0.037	-0.081**	-0.092***	-0.129***	-0.178***	-0.141***	-0.115***	-0.012	-0.060***	-0.059***	-0.079***	-0.090***	-0.079***	-0.064***
	(-1.01)	(-2.37)	(-2.61)	(-3.79)	(-5.13)	(-8.16)	(-3.47)	(-0.73)	(-5.71)	(-5.92)	(-8.17)	(-10.64)	(-4.65)	(-9.92)
HML-G	-0.235***	-0.235***	-0.253***	-0.320***	-0.340***	-0.105**	-0.291***	-0.082**	-0.090***	-0.090***	-0.128***	-0.121***	-0.039	-0.112***
	(-4.66)	(-8.58)	(-10.23)	(-10.63)	(-12.54)	(-2.47)	(-12.05)	(-2.23)	(-5.14)	(-5.29)	(-5.86)	(-5.25)	(-1.16)	(-6.67)
All	0.041	0.022	0.015	-0.040	-0.145***	-0.186***		0.022*	0.005	0.009	-0.017**	-0.079***	-0.101***	
	(1.00)	(0.55)	(0.39)	(-1.09)	(-3.97)	(-11.10)		(1.76)	(0.43)	(0.81)	(-2.03)	(-13.21)	(-6.97)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.002	-0.013	-0.033	-0.097**	-0.171***	-0.173***	-0.093***	0.004	-0.024	-0.018	-0.056***	-0.090***	-0.094***	-0.050***
	(0.04)	(-0.30)	(-0.93)	(-2.44)	(-4.57)	(-7.75)	(-2.61)	(0.24)	(-1.30)	(-1.42)	(-4.05)	(-12.91)	(-5.06)	(-6.64)
Mid	0.108**	0.049	0.052	-0.006	-0.073**	-0.182***	0.030	0.070***	0.020	0.036**	0.005	-0.055***	-0.125***	0.019**
	(2.06)	(1.02)	(1.35)	(-0.15)	(-2.06)	(-6.72)	(0.75)	(3.19)	(1.20)	(2.05)	(0.50)	(-6.05)	(-5.51)	(2.24)
High	0.019	0.067**	0.052	0.039	0.004	-0.015	0.033	-0.018	0.005	0.003	-0.011	-0.037**	-0.019	-0.013
	(0.55)	(2.07)	(1.52)	(1.19)	(0.12)	(-0.82)	(1.07)	(-0.87)	(0.31)	(0.16)	(-0.81)	(-2.38)	(-0.94)	(-1.02)
HML-B	0.018	0.079**	0.084**	0.136***	0.175***	0.157***	0.126***	-0.022	0.029	0.021	0.045**	0.053***	0.076***	0.037**
	(0.42)	(2.34)	(2.50)	(4.71)	(6.64)	(4.74)	(4.99)	(-0.77)	(1.11)	(0.89)	(2.04)	(3.18)	(2.94)	(2.20)
All	0.041	0.022	0.015	-0.040	-0.145***	-0.186***		0.022*	0.005	0.009	-0.017**	-0.079***	-0.101***	
	(1.00)	(0.55)	(0.39)	(-1.09)	(-3.97)	(-11.10)		(1.76)	(0.43)	(0.81)	(-2.03)	(-13.21)	(-6.97)	

Table A.4: Implied Cost of Capital of Portfolios Sorted by Mutual Fund Ownership and ESG Rating: Alternative Ownership Measures (Robustness of Table 5)

In Panel A1, at the end of month t, stocks are first sorted into terciles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 15 (3×5) portfolios. The low-(high)-green-fund-ownership portfolios comprise the bottom (top) tercile of stocks based on the green fund ownership, and the low- (high)-ESG-rating portfolios comprise the bottom (top) quintile of stocks based on the ESG rating. For each of the 15 portfolios, we compute the value-weighted implied cost of capital (ICC) in month $t+1$ and rebalance the portfolios at the end of month $t+1$. We compute the ICC for each stock-month following Hou et al. (2012) and Pástor et al. (2022), and report the time-series averages of the monthly ICCs for each of the 15 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for portfolios sorted only by green fund ownership. The portfolio ICCs are further adjusted by the CAPM. Panel A2 reports similar statistics when we replace green fund ownership with brown fund ownership. We identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. Panel B reports similar statistics based on Fama-French six-factor-adjusted ICCs (FF6) and characteristic-adjusted ICCs per Daniel et al. (1997) (DGTW). The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Monthly Raw and CAPM-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings

Ownership	ICC							CAPM-adjusted ICC						
	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.682***	0.659***	0.675***	0.655***	0.672***	-0.010	0.669***	0.618***	0.596***	0.612***	0.592***	0.609***	-0.008	0.606***
	(35.24)	(34.56)	(32.71)	(37.66)	(33.08)	(-0.81)	(36.93)	(20.99)	(21.11)	(22.49)	(24.18)	(22.78)	(-0.63)	(23.01)
2	0.679***	0.681***	0.671***	0.617***	0.587***	-0.091***	0.642***	0.614***	0.615***	0.607***	0.551***	0.524***	-0.090***	0.576***
	(35.29)	(45.76)	(39.88)	(53.57)	(34.37)	(-7.56)	(50.66)	(25.40)	(24.50)	(26.47)	(30.95)	(21.28)	(-7.20)	(27.66)
High	0.653***	0.597***	0.601***	0.556***	0.499***	-0.154***	0.563***	0.590***	0.533***	0.536***	0.491***	0.433***	-0.156***	0.498***
	(22.85)	(28.78)	(28.05)	(27.62)	(30.21)	(-9.49)	(30.12)	(17.48)	(20.55)	(18.61)	(18.79)	(16.70)	(-9.53)	(18.90)
HML-G	-0.029	-0.062***	-0.074***	-0.099***	-0.173***	-0.143***	-0.105***	-0.028	-0.064***	-0.076***	-0.100***	-0.176***	-0.148***	-0.107***
	(-1.29)	(-3.84)	(-4.22)	(-6.33)	(-14.90)	(-6.04)	(-8.05)	(-1.26)	(-3.97)	(-4.36)	(-6.61)	(-15.46)	(-6.07)	(-8.59)
All	0.651***	0.637***	0.622***	0.587***	0.517***	-0.135***		0.588***	0.574***	0.558***	0.522***	0.452***	-0.136***	
	(29.96)	(31.75)	(30.47)	(37.49)	(29.80)	(-14.57)		(21.09)	(20.19)	(21.31)	(22.23)	(17.91)	(-14.47)	
Panel A2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.653***	0.610***	0.596***	0.542***	0.492***	-0.162***	0.552***	0.591***	0.545***	0.531***	0.476***	0.426***	-0.165***	0.487***
	(24.94)	(28.66)	(31.09)	(30.99)	(32.42)	(-9.76)	(35.18)	(20.14)	(20.63)	(21.83)	(19.23)	(17.37)	(-9.91)	(20.63)
2	0.678***	0.643***	0.633***	0.603***	0.598***	-0.080***	0.628***	0.615***	0.580***	0.570***	0.538***	0.534***	-0.081***	0.564***
	(29.67)	(27.20)	(33.63)	(30.01)	(32.17)	(-5.32)	(32.96)	(20.11)	(19.03)	(23.24)	(18.85)	(21.88)	(-5.22)	(21.32)
High	0.660***	0.669***	0.667***	0.674***	0.646***	-0.015	0.662***	0.598***	0.605***	0.603***	0.611***	0.581***	-0.017	0.598***
	(33.18)	(35.21)	(36.09)	(37.27)	(41.60)	(-1.21)	(39.65)	(20.94)	(21.63)	(20.88)	(24.18)	(25.55)	(-1.43)	(23.36)
HML-B	0.007	0.060***	0.072***	0.132***	0.154***	0.147***	0.110***	0.007	0.059***	0.071***	0.135***	0.155***	0.148***	0.112***
	(0.30)	(3.49)	(4.06)	(8.39)	(13.06)	(6.29)	(9.69)	(0.31)	(3.28)	(4.01)	(8.84)	(13.09)	(6.42)	(9.73)
All	0.651***	0.637***	0.622***	0.587***	0.517***	-0.135***		0.588***	0.574***	0.558***	0.522***	0.452***	-0.136***	
	(29.96)	(31.75)	(30.47)	(37.49)	(29.80)	(-14.57)		(21.09)	(20.19)	(21.31)	(22.23)	(17.91)	(-14.47)	

Panel B: Monthly FF6- and DGTW-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings

Ownership	FF6-adjusted ICC							DGTW-adjusted ICC						
	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel B1: Portfolios Sorted by Green Fund Ownership and ESG Rating														
Low	0.612***	0.592***	0.609***	0.589***	0.606***	-0.006	0.602***	0.036***	0.021***	0.016***	0.000	0.024***	-0.012	0.020***
	(21.47)	(22.21)	(23.34)	(25.31)	(23.90)	(-0.44)	(24.08)	(3.35)	(3.15)	(2.67)	(0.02)	(3.21)	(-1.13)	(3.69)
2	0.612***	0.614***	0.606***	0.549***	0.521***	-0.092***	0.574***	0.047***	0.068***	0.043***	0.012	-0.020***	-0.067***	0.030***
	(27.12)	(25.25)	(27.27)	(32.72)	(23.34)	(-7.66)	(29.29)	(4.45)	(8.41)	(6.20)	(1.38)	(-2.86)	(-7.80)	(4.20)
High	0.589***	0.536***	0.537***	0.491***	0.435***	-0.154***	0.500***	0.037***	0.004	0.000	-0.031***	-0.061***	-0.098***	-0.021***
	(18.41)	(21.20)	(19.27)	(19.48)	(16.84)	(-9.95)	(19.40)	(3.63)	(1.05)	(0.02)	(-4.85)	(-13.62)	(-7.43)	(-9.43)
HML-G	-0.023	-0.057***	-0.072***	-0.098***	-0.171***	-0.149***	-0.102***	0.002	-0.017*	-0.016*	-0.031***	-0.085***	-0.086***	-0.041***
	(-1.05)	(-3.74)	(-4.18)	(-6.77)	(-16.56)	(-6.39)	(-8.74)	(0.10)	(-1.94)	(-1.83)	(-3.27)	(-9.26)	(-4.53)	(-6.03)
All	0.587***	0.573***	0.561***	0.521***	0.452***	-0.135***		0.033***	0.021***	0.022***	-0.008**	-0.050***	-0.084***	
	(22.09)	(20.81)	(21.72)	(23.01)	(18.35)	(-14.78)		(7.74)	(4.59)	(5.26)	(-2.11)	(-16.28)	(-13.49)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating														
Low	0.589***	0.548***	0.532***	0.477***	0.428***	-0.161***	0.488***	0.042***	0.009	0.005	-0.034***	-0.063***	-0.105***	-0.026***
	(21.58)	(21.44)	(22.36)	(20.18)	(17.59)	(-10.21)	(21.28)	(3.85)	(1.27)	(0.79)	(-5.29)	(-12.92)	(-7.74)	(-6.86)
2	0.615***	0.580***	0.570***	0.536***	0.533***	-0.082***	0.563***	0.048***	0.021**	0.011	-0.017**	-0.028***	-0.076***	0.005
	(21.10)	(19.79)	(23.50)	(19.15)	(21.88)	(-5.67)	(21.76)	(6.62)	(2.44)	(1.64)	(-2.41)	(-3.99)	(-8.34)	(1.04)
High	0.597***	0.604***	0.604***	0.609***	0.579***	-0.018	0.598***	0.020*	0.027***	0.028***	0.030***	0.012*	-0.009	0.023***
	(21.11)	(21.90)	(21.11)	(24.64)	(25.93)	(-1.44)	(23.60)	(1.87)	(3.00)	(3.52)	(3.34)	(1.94)	(-0.90)	(3.53)
HML-B	0.008	0.056***	0.072***	0.132***	0.152***	0.144***	0.110***	-0.022	0.018	0.022*	0.064***	0.075***	0.096***	0.049***
	(0.35)	(3.25)	(4.09)	(8.58)	(12.99)	(6.13)	(9.76)	(-1.15)	(1.24)	(1.82)	(5.31)	(8.55)	(4.96)	(5.22)
All	0.587***	0.573***	0.561***	0.521***	0.452***	-0.135***		0.033***	0.021***	0.022***	-0.008**	-0.050***	-0.084***	
	(22.09)	(20.81)	(21.72)	(23.01)	(18.35)	(-14.78)		(7.74)	(4.59)	(5.26)	(-2.11)	(-16.28)	(-13.49)	

Table A.5: Performance of Portfolios Sorted by Mutual Fund Ownership and ESG Rating: Extended Sample Period (Robustness of Table 5)

In Panels A1 and A2, at the end of month t, stocks are first sorted into quintiles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low- (high)-ESG-rating and green-fund-ownership portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and green fund ownership, respectively. For each of the 25 portfolios, we compute the value-weighted return in month t+1 and rebalance the portfolios at the end of month t+1. We report the time-series averages of the monthly returns for each of the 25 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for the portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for the portfolios sorted only by green fund ownership. The portfolio returns are further adjusted by the CAPM. Panels A1 and A2 report the subperiod results for January 2001–October 2012 and for November 2012–December 2021, respectively. Panels A3 and A4 report similar statistics when we replace green fund ownership with brown fund ownership. Panel B reports similar statistics based on Fama-French six-factor-adjusted returns (FF6) and characteristic-adjusted returns per Daniel et al. (1997) (DGTW). We compute the average rank across MSCI KLD, MSCI ESG Ratings, and Sustainalytics to obtain the firm-level ESG rating, and identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Monthly Raw and CAPM-adjusted Returns Sorted by Mutual Fund Ownership and ESG Ratings

	Return							CAPM-adjusted Return						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.879	0.806	0.421	0.664	0.579	-0.299	0.751	0.474*	0.411	0.066	0.272	0.202	-0.272	0.353
	(1.43)	(1.34)	(0.78)	(1.27)	(1.13)	(-0.95)	(1.37)	(1.77)	(1.48)	(0.19)	(1.09)	(0.71)	(-0.89)	(1.64)
2	0.847	1.018	0.815	0.411	0.952**	0.105	0.731	0.447*	0.596*	0.409	0.042	0.578***	0.131	0.337*
	(1.50)	(1.52)	(1.17)	(0.83)	(2.12)	(0.33)	(1.41)	(1.97)	(1.73)	(0.95)	(0.15)	(2.65)	(0.44)	(1.89)
3	0.639	0.366	0.500	0.155	0.502	-0.137	0.476	0.244	-0.032	0.112	-0.238	0.118	-0.126	0.081
	(1.15)	(0.69)	(0.95)	(0.28)	(1.11)	(-0.47)	(0.94)	(1.09)	(-0.16)	(0.54)	(-1.34)	(0.62)	(-0.44)	(0.60)
4	0.491	0.399	0.459	0.330	0.320	-0.171	0.410	0.122	0.001	0.087	-0.064	-0.094	-0.216	0.026
	(1.04)	(0.78)	(0.97)	(0.62)	(0.63)	(-0.64)	(0.91)	(0.71)	(0.00)	(0.57)	(-0.30)	(-0.52)	(-0.81)	(0.27)
High	0.700	0.328	0.492	0.159	0.061	-0.638**	0.231	0.285	-0.037	0.087	-0.228	-0.304**	-0.588**	-0.158
	(1.31)	(0.72)	(0.93)	(0.31)	(0.13)	(-2.48)	(0.49)	(1.30)	(-0.17)	(0.50)	(-1.13)	(-2.19)	(-2.31)	(-1.63)
HML-G	-0.179	-0.479	0.071	-0.505	-0.518	-0.339	-0.521**	-0.190	-0.448	0.021	-0.501	-0.506	-0.316	-0.512**
	(-0.59)	(-1.30)	(0.18)	(-1.51)	(-1.58)	(-0.99)	(-2.09)	(-0.61)	(-1.25)	(0.05)	(-1.44)	(-1.50)	(-0.90)	(-1.99)
All	0.596	0.279	0.370	0.230	0.305	-0.290		0.224*	-0.125	-0.007	-0.143	-0.069	-0.293	
	(1.29)	(0.57)	(0.78)	(0.51)	(0.72)	(-1.51)		(1.75)	(-0.78)	(-0.08)	(-1.21)	(-0.89)	(-1.51)	
Panel A2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	1.251**	0.758	1.194**	0.567	0.806	-0.445	1.002*	-0.489	-0.673**	-0.386	-0.938**	-0.853***	-0.364	-0.607**
	(2.18)	(1.51)	(2.04)	(1.19)	(1.56)	(-1.61)	(1.92)	(-1.54)	(-2.16)	(-1.07)	(-2.43)	(-2.67)	(-1.13)	(-2.02)
2	1.278**	0.941**	1.051**	1.239**	1.291**	0.014	1.224**	-0.297	-0.477**	-0.507*	-0.489	-0.525*	-0.228	-0.430*
	(2.59)	(2.58)	(2.35)	(2.23)	(2.28)	(0.04)	(2.54)	(-0.83)	(-2.10)	(-1.74)	(-1.48)	(-1.67)	(-0.52)	(-1.79)
3	1.283**	1.588***	1.032**	0.945**	1.366***	0.084	1.316***	-0.322	0.002	-0.502*	-0.685***	-0.279	0.043	-0.327*
	(2.46)	(3.61)	(2.37)	(2.08)	(2.76)	(0.28)	(2.95)	(-1.10)	(0.01)	(-1.77)	(-2.79)	(-1.21)	(0.16)	(-1.73)
4	1.519***	1.751***	1.574***	1.247***	1.629***	0.111	1.533***	0.090	0.357	0.054	-0.288	0.008	-0.082	0.044
	(3.88)	(4.39)	(4.01)	(2.97)	(3.40)	(0.28)	(4.28)	(0.40)	(1.50)	(0.29)	(-1.31)	(0.03)	(-0.22)	(0.34)
High	1.277***	1.204***	0.958***	1.171***	1.626***	0.349*	1.356***	-0.157	-0.111	-0.348**	-0.127	0.421***	0.578***	0.054
	(3.63)	(3.77)	(3.03)	(3.91)	(5.48)	(1.69)	(4.68)	(-1.24)	(-0.85)	(-2.12)	(-0.99)	(3.15)	(3.08)	(0.94)
HML-G	0.025	0.446	-0.236	0.604*	0.819*	0.794**	0.355	0.332	0.563*	0.037	0.811**	1.274***	0.942**	0.661*
	(0.07)	(1.23)	(-0.52)	(1.73)	(1.94)	(2.50)	(0.97)	(1.03)	(1.69)	(0.10)	(2.00)	(3.09)	(2.52)	(1.93)
All	1.375***	1.407***	1.115***	1.092***	1.482***	0.107		-0.090	-0.083	-0.172	-0.293**	0.180**	0.270	
	(3.72)	(3.81)	(3.30)	(3.41)	(5.10)	(0.57)		(-0.54)	(-0.51)	(-1.33)	(-2.13)	(2.57)	(1.41)	
Panel A3: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.799**	0.363	0.675	0.615	0.241	-0.558*	0.377	0.455**	-0.006	0.302	0.246	-0.124	-0.579*	0.015
	(2.29)	(0.69)	(1.32)	(1.28)	(0.50)	(-1.67)	(0.89)	(2.15)	(-0.03)	(0.82)	(0.95)	(-0.56)	(-1.78)	(0.11)
2	0.579	0.261	0.238	0.274	0.191	-0.389*	0.291	0.218	-0.143	-0.153	-0.106	-0.222	-0.440**	-0.106
	(1.34)	(0.50)	(0.48)	(0.53)	(0.39)	(-1.71)	(0.62)	(1.09)	(-0.62)	(-0.78)	(-0.45)	(-1.41)	(-2.05)	(-0.84)
3	0.638	0.356	0.174	0.296	0.457	-0.182	0.466	0.241	-0.064	-0.205	-0.105	0.072	-0.169	0.071
	(1.14)	(0.64)	(0.37)	(0.50)	(1.00)	(-0.70)	(0.94)	(1.15)	(-0.29)	(-1.46)	(-0.42)	(0.50)	(-0.66)	(0.68)
4	0.834	0.559	0.417	0.479	0.547	-0.287	0.613	0.445**	0.140	0.026	0.084	0.167	-0.278	0.217
	(1.58)	(0.98)	(0.79)	(0.87)	(1.14)	(-1.27)	(1.19)	(2.08)	(0.68)	(0.13)	(0.40)	(0.97)	(-1.22)	(1.52)
High	0.614	0.492	0.461	0.700	0.315	-0.299	0.513	0.222	0.090	0.049	0.284	-0.081	-0.303	0.110
	(1.05)	(0.88)	(0.73)	(1.23)	(0.59)	(-1.27)	(0.91)	(0.81)	(0.40)	(0.19)	(1.49)	(-0.40)	(-1.27)	(0.56)
HML-B	-0.186	0.130	-0.214	0.085	0.074	0.259	0.136	-0.233	0.096	-0.252	0.038	0.043	0.276	0.096
	(-0.47)	(0.41)	(-0.41)	(0.22)	(0.22)	(0.66)	(0.45)	(-0.64)	(0.30)	(-0.50)	(0.10)	(0.13)	(0.72)	(0.34)
All	0.596	0.279	0.370	0.230	0.305	-0.290		0.224*	-0.125	-0.007	-0.143	-0.069	-0.293	
	(1.29)	(0.57)	(0.78)	(0.51)	(0.72)	(-1.51)		(1.75)	(-0.78)	(-0.08)	(-1.21)	(-0.89)	(-1.51)	
Panel A4: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	1.345***	1.251***	1.003***	1.270***	1.615***	0.271	1.364***	0.029	-0.063	-0.329**	-0.080	0.405***	0.377*	0.057
	(4.00)	(3.72)	(3.15)	(4.31)	(5.49)	(1.21)	(4.70)	(0.17)	(-0.45)	(-2.35)	(-0.77)	(3.13)	(1.83)	(1.09)
2	1.548***	1.538***	0.918**	1.647***	1.186***	-0.362	1.409***	-0.010	0.113	-0.518*	0.141	-0.345***	-0.336	-0.111
	(3.31)	(3.53)	(2.31)	(4.28)	(3.24)	(-1.36)	(3.71)	(-0.04)	(0.41)	(-1.84)	(0.88)	(-2.67)	(-1.36)	(-0.78)
3	1.311***	1.238***	1.225***	1.307***	1.252***	-0.060	1.325***	-0.402*	-0.356	-0.205	-0.356*	-0.296	0.105	-0.303*
	(2.73)	(2.74)	(3.08)	(2.73)	(2.93)	(-0.31)	(3.02)	(-1.90)	(-1.54)	(-0.83)	(-1.69)	(-1.54)	(0.55)	(-1.75)
4	1.307***	1.402***	1.055**	1.441***	1.211***	-0.096	1.367***	-0.247	-0.224	-0.321	-0.317	-0.309	-0.062	-0.240
	(3.02)	(2.90)	(2.61)	(2.74)	(2.69)	(-0.51)	(2.93)	(-1.05)	(-0.78)	(-1.29)	(-1.06)	(-1.21)	(-0.34)	(-0.96)
High	1.192**	1.338***	0.872**	1.219**	1.356***	0.164	1.278***	-0.405	-0.249	-0.594**	-0.384	-0.230	0.175	-0.332
	(2.47)	(2.86)	(2.20)	(2.57)	(3.06)	(0.93)	(2.78)	(-1.54)	(-0.94)	(-2.04)	(-1.59)	(-1.17)	(0.97)	(-1.45)
HML-B	-0.153	0.087	-0.132	-0.051	-0.259	-0.106	-0.086	-0.434	-0.187	-0.265	-0.304	-0.636**	-0.202	-0.388
	(-0.50)	(0.30)	(-0.55)	(-0.18)	(-0.79)	(-0.38)	(-0.31)	(-1.42)	(-0.64)	(-1.05)	(-1.02)	(-2.23)	(-0.81)	(-1.44)
All	1.375***	1.407***	1.115***	1.092***	1.482***	0.107		-0.090	-0.083	-0.172	-0.293**	0.180**	0.270	
	(3.72)	(3.81)	(3.30)	(3.41)	(5.10)	(0.57)		(-0.54)	(-0.51)	(-1.33)	(-2.13)	(2.57)	(1.41)	

Table A.5 (continued)

Panel B: Monthly FF6- and DGTW-adjusted Returns Sorted by Mutual Fund Ownership and ESG Ratings

Ownership	FF6-adjusted Return							DGTW-adjusted Return						
	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel B1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	-0.022	-0.189	-0.492	-0.205	-0.297	-0.275	-0.209	0.100	0.176	-0.111	0.008	-0.202	-0.302	-0.006
	(-0.09)	(-0.68)	(-1.43)	(-1.21)	(-1.61)	(-0.87)	(-1.55)	(0.45)	(1.06)	(-0.32)	(0.04)	(-0.94)	(-1.15)	(-0.04)
2	-0.097	0.249	-0.170	-0.408	0.135	0.232	-0.125	0.128	0.409	0.148	-0.142	0.276	0.148	0.028
	(-0.43)	(0.53)	(-0.68)	(-1.57)	(0.83)	(0.76)	(-0.78)	(0.66)	(1.49)	(0.38)	(-0.57)	(1.19)	(0.52)	(0.18)
3	-0.118	-0.085	-0.264	-0.363*	-0.219	-0.100	-0.197	-0.018	-0.027	-0.102	-0.296*	-0.033	-0.015	-0.099
	(-0.50)	(-0.41)	(-1.23)	(-1.93)	(-1.17)	(-0.35)	(-1.38)	(-0.12)	(-0.13)	(-0.60)	(-1.84)	(-0.15)	(-0.06)	(-0.88)
4	0.145	0.287	0.176	-0.154	0.072	-0.074	0.152	0.069	-0.007	-0.088	-0.175	-0.028	-0.098	-0.006
	(0.86)	(1.12)	(0.99)	(-0.67)	(0.37)	(-0.26)	(1.64)	(0.41)	(-0.04)	(-0.64)	(-0.97)	(-0.18)	(-0.51)	(-0.06)
High	0.345*	-0.128	0.302*	0.104	-0.285*	-0.630**	-0.037	0.240	-0.058	0.067	-0.229	-0.250*	-0.489*	-0.122
	(1.68)	(-0.56)	(1.87)	(0.51)	(-1.67)	(-2.43)	(-0.34)	(1.12)	(-0.49)	(0.50)	(-1.44)	(-1.70)	(-1.83)	(-1.30)
HML-G	0.368	0.061	0.793*	0.309	0.012	-0.355	0.171	0.139	-0.234	0.178	-0.237	-0.048	-0.187	-0.116
	(1.25)	(0.18)	(1.97)	(1.24)	(0.05)	(-0.94)	(0.97)	(0.63)	(-1.35)	(0.46)	(-1.04)	(-0.20)	(-0.60)	(-0.81)
All	0.002	-0.004	0.012	-0.189	0.025	0.023		0.102	0.009	-0.060	-0.133	-0.022	-0.124	
	(0.01)	(-0.03)	(0.13)	(-1.39)	(0.28)	(0.12)		(0.77)	(0.07)	(-0.67)	(-1.40)	(-0.24)	(-0.90)	
Panel B2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	-0.085	-0.332	0.066	-0.712**	-0.528***	-0.443	-0.231	0.402**	-0.063	0.238	-0.075	-0.085	-0.487**	0.061
	(-0.32)	(-1.59)	(0.28)	(-2.25)	(-2.77)	(-1.42)	(-1.49)	(2.15)	(-0.38)	(1.46)	(-0.39)	(-0.46)	(-2.06)	(0.54)
2	-0.098	-0.216	-0.211	-0.189	-0.264	-0.166	-0.143	0.184	-0.051	0.008	0.076	0.163	-0.021	0.075
	(-0.29)	(-1.08)	(-0.77)	(-1.22)	(-1.62)	(-0.44)	(-1.42)	(0.74)	(-0.28)	(0.05)	(0.44)	(0.96)	(-0.07)	(0.70)
3	-0.077	0.204	-0.345*	-0.491**	-0.015	0.063	-0.093	0.026	0.219	0.033	-0.032	0.198	0.172	0.082
	(-0.30)	(1.13)	(-1.72)	(-2.50)	(-0.08)	(0.24)	(-1.01)	(0.11)	(1.29)	(0.26)	(-0.32)	(1.23)	(0.61)	(1.06)
4	0.088	0.450**	0.101	-0.254	-0.166	-0.254	0.015	0.227	0.406**	0.142	0.104	0.352	0.126	0.222**
	(0.37)	(2.32)	(0.51)	(-1.28)	(-0.69)	(-0.63)	(0.15)	(1.20)	(2.02)	(1.21)	(0.54)	(1.31)	(0.33)	(2.09)
High	-0.161	-0.069	-0.255	-0.082	0.257**	0.418**	0.018	0.068	0.038	0.011	0.003	0.284***	0.216	0.112***
	(-1.29)	(-0.67)	(-1.53)	(-0.79)	(2.57)	(2.25)	(0.58)	(0.67)	(0.39)	(0.15)	(0.04)	(2.90)	(1.29)	(2.85)
HML-G	-0.076	0.263	-0.321	0.630*	0.785***	0.861**	0.249	-0.335**	0.101	-0.227	0.078	0.369*	0.703***	0.051
	(-0.28)	(1.07)	(-1.17)	(1.97)	(3.51)	(2.50)	(1.50)	(-2.17)	(0.54)	(-1.34)	(0.38)	(1.79)	(2.78)	(0.43)
All	-0.016	0.016	-0.216	-0.178	0.094**	0.111		0.146	0.132	0.070	-0.023	0.206***	0.060	
	(-0.11)	(0.12)	(-1.48)	(-1.58)	(2.10)	(0.71)		(1.10)	(1.09)	(1.01)	(-0.38)	(3.71)	(0.39)	
Panel B3: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.436*	-0.265	0.451	0.311	-0.150	-0.586**	0.109	0.376	-0.109	0.212	0.143	-0.164	-0.540*	0.061
	(1.84)	(-1.19)	(1.17)	(1.08)	(-0.67)	(-2.06)	(0.75)	(1.61)	(-0.63)	(0.84)	(0.62)	(-0.89)	(-1.86)	(0.48)
2	0.216	-0.269	0.042	-0.024	-0.066	-0.282	0.023	0.058	-0.213	-0.126	-0.239	-0.144	-0.202	-0.127
	(1.00)	(-1.19)	(0.24)	(-0.09)	(-0.40)	(-1.13)	(0.18)	(0.33)	(-1.29)	(-0.85)	(-1.07)	(-1.31)	(-1.01)	(-1.50)
3	-0.010	0.193	-0.315**	-0.310	-0.055	-0.045	-0.034	0.113	0.080	-0.247*	-0.191	0.002	-0.111	-0.011
	(-0.04)	(0.83)	(-2.09)	(-1.29)	(-0.35)	(-0.15)	(-0.30)	(0.59)	(0.47)	(-1.88)	(-0.94)	(0.01)	(-0.50)	(-0.11)
4	0.134	-0.064	-0.250	-0.129	-0.222	-0.356	-0.047	0.202	0.074	-0.183	0.006	0.077	-0.124	0.080
	(0.58)	(-0.29)	(-1.37)	(-0.55)	(-1.45)	(-1.51)	(-0.32)	(1.25)	(0.48)	(-1.04)	(0.04)	(0.40)	(-0.53)	(0.75)
High	-0.294	-0.276	-0.330	-0.067	-0.541**	-0.246	-0.307*	0.081	-0.077	-0.104	0.123	-0.325*	-0.406*	-0.033
	(-1.24)	(-1.39)	(-1.31)	(-0.32)	(-2.47)	(-1.03)	(-1.71)	(0.42)	(-0.36)	(-0.51)	(0.78)	(-1.78)	(-1.86)	(-0.22)
HML-B	-0.731*	-0.011	-0.781	-0.378	-0.391	0.340	-0.416	-0.296	0.033	-0.316	-0.020	-0.162	0.134	-0.094
	(-1.96)	(-0.03)	(-1.46)	(-0.94)	(-1.15)	(1.02)	(-1.44)	(-1.10)	(0.12)	(-0.87)	(-0.08)	(-0.66)	(0.42)	(-0.50)
All	0.002	-0.004	0.012	-0.189	0.025	0.023		0.102	0.009	-0.060	-0.133	-0.022	-0.124	
	(0.01)	(-0.03)	(0.13)	(-1.39)	(0.28)	(0.12)		(0.77)	(0.07)	(-0.67)	(-1.40)	(-0.24)	(-0.90)	
Panel B4: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	-0.021	-0.076	-0.219*	-0.124	0.250**	0.272	-0.003	0.055	0.074	-0.067	0.062	0.286***	0.230	0.103***
	(-0.12)	(-0.55)	(-1.89)	(-1.26)	(2.57)	(1.32)	(-0.12)	(0.37)	(0.93)	(-0.92)	(0.85)	(3.01)	(1.21)	(3.08)
2	0.139	0.308	-0.437*	0.310**	-0.177*	-0.316	0.074	0.322	0.226	0.056	0.336**	-0.070	-0.392*	0.153
	(0.64)	(1.47)	(-1.83)	(2.54)	(-1.66)	(-1.33)	(0.88)	(1.53)	(1.06)	(0.41)	(2.20)	(-0.66)	(-1.75)	(1.35)
3	-0.079	-0.129	-0.133	-0.228	-0.109	-0.030	-0.100	0.209	0.008	0.304**	0.078	0.123	-0.086	0.132
	(-0.52)	(-0.94)	(-0.49)	(-1.56)	(-0.87)	(-0.16)	(-1.28)	(1.27)	(0.06)	(2.12)	(0.46)	(0.90)	(-0.44)	(1.37)
4	0.034	0.097	-0.200	-0.069	-0.104	-0.138	0.023	0.078	0.207	0.203*	0.213	0.164	0.087	0.183**
	(0.25)	(0.60)	(-0.80)	(-0.43)	(-0.75)	(-0.80)	(0.21)	(0.59)	(1.62)	(1.73)	(1.50)	(1.30)	(0.53)	(2.30)
High	-0.159	0.048	-0.453*	-0.110	0.026	0.184	-0.062	0.079	0.057	0.079	-0.003	0.242**	0.163	0.093
	(-0.95)	(0.33)	(-1.68)	(-0.91)	(0.26)	(0.98)	(-0.69)	(0.57)	(0.38)	(0.64)	(-0.02)	(2.09)	(0.95)	(0.96)
HML-B	-0.137	0.124	-0.234	0.014	-0.225*	-0.088	-0.059	0.024	-0.016	0.146	-0.065	-0.043	-0.067	-0.010
	(-0.61)	(0.66)	(-0.96)	(0.08)	(-1.74)	(-0.36)	(-0.60)	(0.12)	(-0.10)	(1.26)	(-0.51)	(-0.36)	(-0.28)	(-0.12)
All	-0.016	0.016	-0.216	-0.178	0.094**	0.111		0.146	0.132	0.070	-0.023	0.206***	0.060	
	(-0.11)	(0.12)	(-1.48)	(-1.58)	(2.10)	(0.71)		(1.10)	(1.09)	(1.01)	(-0.38)	(3.71)	(0.39)	

Table A.6: Implied Cost of Capital of Portfolios Sorted by Mutual Fund Ownership and ESG Rating: Extended Sample Period (Robustness of Table 5)

In Panels A1 and A2, at the end of month t, stocks are first sorted into quintiles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low- (high)-ESG-rating and green-fund-ownership portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and green fund ownership, respectively. For each of the 25 portfolios, we compute the value-weighted implied cost of capital (ICC) in month t+1 and rebalance the portfolios at the end of month t+1. We compute the ICC for each stock-month following Hou et al. (2012), and report the time-series averages of the monthly ICCs for each of the 25 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for portfolios sorted only by green fund ownership. The portfolio ICCs are further adjusted by the CAPM. Panels A1 and A2 report the subperiod results for January 2001–October 2012 and for November 2012–December 2021, respectively. Panels A3 and A4 report similar statistics when we replace green fund ownership with brown fund ownership. Panel B reports similar statistics based on Fama-French six-factor-adjusted returns (FF6) and characteristic-adjusted returns per Daniel et al. (1997) (DGTW). We compute the average rank across MSCI KLD, MSCI ESG Ratings, and Sustainalytics to obtain the firm-level ESG rating, and identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table A.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Monthly Raw and CAPM-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings

Ownership	ICC							CAPM-adjusted ICC						
	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.751***	0.616***	0.548***	0.698***	0.726***	-0.025**	0.727***	0.600***	0.464***	0.396***	0.547***	0.574***	-0.026**	0.574***
	(55.98)	(16.17)	(10.84)	(25.37)	(56.56)	(-2.11)	(61.40)	(19.84)	(9.90)	(6.93)	(15.47)	(19.51)	(-2.27)	(19.75)
2	0.701***	0.661***	0.607***	0.618***	0.714***	0.013	0.692***	0.548***	0.508***	0.454***	0.465***	0.562***	0.013	0.539***
	(34.50)	(25.75)	(15.56)	(18.05)	(61.09)	(0.74)	(47.08)	(16.39)	(12.30)	(8.41)	(11.19)	(20.39)	(0.78)	(17.32)
3	0.699***	0.671***	0.649***	0.609***	0.720***	0.020	0.691***	0.547***	0.518***	0.497***	0.457***	0.567***	0.020	0.538***
	(32.70)	(26.12)	(26.78)	(19.05)	(53.87)	(1.13)	(48.40)	(15.15)	(12.62)	(11.92)	(11.34)	(20.15)	(1.12)	(17.02)
4	0.685***	0.629***	0.679***	0.637***	0.652***	-0.033*	0.648***	0.533***	0.476***	0.526***	0.485***	0.499***	-0.033**	0.495***
	(36.12)	(33.96)	(39.57)	(26.71)	(33.20)	(-1.94)	(40.44)	(14.27)	(16.12)	(15.84)	(12.88)	(14.52)	(-1.98)	(15.28)
High	0.701***	0.614***	0.649***	0.618***	0.553***	-0.147***	0.614***	0.548***	0.461***	0.496***	0.466***	0.401***	-0.147***	0.462***
	(35.92)	(16.95)	(42.38)	(47.76)	(55.68)	(-11.54)	(48.08)	(15.91)	(9.87)	(14.78)	(14.73)	(14.57)	(-11.43)	(14.92)
HML-G	-0.051**	-0.003	0.100*	-0.080***	-0.173***	-0.122***	-0.112***	-0.051**	-0.003	0.100*	-0.081***	-0.173***	-0.121***	-0.113***
	(-2.54)	(-0.05)	(1.96)	(-2.61)	(-12.34)	(-7.01)	(-7.32)	(-2.58)	(-0.06)	(1.95)	(-2.68)	(-12.45)	(-7.03)	(-7.36)
All	0.681***	0.608***	0.620***	0.581***	0.578***	-0.103***		0.528***	0.455***	0.467***	0.429***	0.425***	-0.103***	
	(37.33)	(19.30)	(19.00)	(18.17)	(56.74)	(-10.43)		(14.86)	(9.13)	(9.91)	(10.35)	(14.45)	(-10.38)	
Panel A2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	0.504***	0.460***	0.511***	0.465***	0.494***	-0.010	0.500***	0.458***	0.415***	0.466***	0.421***	0.445***	-0.013	0.453***
	(17.65)	(11.49)	(17.40)	(14.63)	(17.96)	(-0.88)	(18.19)	(15.04)	(10.98)	(16.33)	(15.99)	(16.52)	(-1.09)	(16.90)
2	0.584***	0.566***	0.499***	0.542***	0.569***	-0.015	0.569***	0.532***	0.520***	0.451***	0.492***	0.518***	-0.014	0.518***
	(50.76)	(45.22)	(16.21)	(28.88)	(41.75)	(-1.14)	(57.23)	(28.78)	(28.12)	(14.42)	(25.07)	(35.00)	(-1.02)	(31.99)
3	0.571***	0.523***	0.533***	0.525***	0.592***	0.022**	0.564***	0.521***	0.470***	0.486***	0.473***	0.543***	0.022**	0.512***
	(39.96)	(43.49)	(31.23)	(16.00)	(51.31)	(2.05)	(61.50)	(20.68)	(21.84)	(27.59)	(14.97)	(27.58)	(2.31)	(27.20)
4	0.555***	0.507***	0.530***	0.514***	0.519***	-0.037	0.510***	0.502***	0.457***	0.482***	0.464***	0.469***	-0.033	0.459***
	(34.19)	(28.70)	(27.75)	(31.92)	(23.47)	(-1.46)	(33.43)	(19.68)	(20.87)	(20.79)	(29.40)	(25.45)	(-1.25)	(24.90)
High	0.523***	0.570***	0.523***	0.529***	0.442***	-0.080***	0.511***	0.473***	0.523***	0.476***	0.480***	0.391***	-0.082***	0.462***
	(20.31)	(32.05)	(14.55)	(29.47)	(25.80)	(-5.43)	(29.33)	(14.61)	(25.28)	(13.47)	(19.41)	(14.39)	(-5.60)	(18.56)
HML-G	0.018	0.110***	0.013	0.064*	-0.052	-0.070***	0.011	0.015	0.108***	0.010	0.059*	-0.054	-0.069***	0.009
	(0.41)	(3.30)	(0.26)	(1.76)	(-1.48)	(-3.88)	(0.30)	(0.36)	(3.44)	(0.23)	(1.71)	(-1.60)	(-3.64)	(0.26)
All	0.539***	0.520***	0.519***	0.537***	0.485***	-0.054***		0.488***	0.468***	0.475***	0.488***	0.435***	-0.053***	
	(32.51)	(32.46)	(18.95)	(20.55)	(32.00)	(-5.74)		(20.34)	(17.71)	(17.30)	(18.43)	(18.51)	(-5.74)	
Panel A3: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.610***	0.616***	0.531***	0.609***	0.548***	-0.062***	0.580***	0.457***	0.464***	0.378***	0.457***	0.396***	-0.061***	0.428***
	(26.53)	(18.56)	(13.91)	(40.62)	(51.82)	(-3.49)	(45.75)	(12.41)	(11.62)	(8.48)	(15.08)	(15.10)	(-3.51)	(14.58)
2	0.646***	0.630***	0.593***	0.633***	0.617***	-0.029***	0.635***	0.493***	0.477***	0.441***	0.481***	0.464***	-0.029***	0.482***
	(23.22)	(20.45)	(17.50)	(32.96)	(28.24)	(-2.78)	(27.99)	(12.11)	(11.77)	(8.25)	(13.81)	(13.08)	(-2.74)	(13.03)
3	0.671***	0.602***	0.604***	0.602***	0.658***	-0.013	0.658***	0.517***	0.450***	0.451***	0.449***	0.505***	-0.012	0.505***
	(31.05)	(17.97)	(18.20)	(19.37)	(39.34)	(-1.04)	(38.84)	(13.30)	(9.06)	(9.43)	(11.00)	(15.70)	(-1.01)	(14.97)
4	0.711***	0.690***	0.638***	0.653***	0.722***	0.010	0.695***	0.558***	0.538***	0.486***	0.501***	0.569***	0.011	0.543***
	(48.21)	(48.55)	(27.59)	(26.52)	(56.13)	(0.84)	(60.30)	(18.04)	(19.64)	(14.48)	(13.60)	(21.58)	(0.89)	(18.93)
High	0.744***	0.705***	0.673***	0.724***	0.731***	-0.013	0.721***	0.591***	0.553***	0.521***	0.571***	0.579***	-0.013	0.569***
	(54.84)	(50.37)	(27.80)	(55.62)	(55.49)	(-1.61)	(58.51)	(19.83)	(17.57)	(15.10)	(18.03)	(19.72)	(-1.61)	(18.83)
HML-B	0.134***	0.090***	0.142***	0.114***	0.183***	0.049***	0.141***	0.135***	0.089**	0.143***	0.114***	0.183***	0.048***	0.141***
	(5.13)	(2.62)	(3.13)	(6.55)	(11.04)	(2.72)	(8.23)	(5.21)	(2.61)	(3.13)	(6.55)	(11.07)	(2.71)	(8.28)
All	0.681***	0.608***	0.620***	0.581***	0.578***	-0.103***		0.528***	0.455***	0.467***	0.429***	0.425***	-0.103***	
	(37.33)	(19.30)	(19.00)	(18.17)	(56.74)	(-10.43)		(14.86)	(9.13)	(9.91)	(10.35)	(14.45)	(-10.38)	
Panel A4: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	0.535***	0.520***	0.533***	0.533***	0.441***	-0.094***	0.508***	0.483***	0.472***	0.485***	0.483***	0.390***	-0.093***	0.458***
	(25.52)	(18.09)	(19.82)	(33.76)	(25.85)	(-6.82)	(32.78)	(15.47)	(15.62)	(17.68)	(22.79)	(14.31)	(-6.61)	(19.74)
2	0.518***	0.533***	0.530***	0.532***	0.545***	0.027*	0.538***	0.466***	0.482***	0.487***	0.478***	0.494***	0.028**	0.487***
	(28.50)	(30.11)	(18.59)	(31.37)	(41.01)	(1.90)	(39.08)	(21.48)	(21.12)	(18.75)	(24.93)	(25.69)	(2.07)	(26.49)
3	0.545***	0.509***	0.481***	0.501***	0.502***	-0.043***	0.517***	0.498***	0.460***	0.436***	0.455***	0.452***	-0.046***	0.469***
	(44.07)	(37.89)	(13.29)	(32.48)	(38.37)	(-4.23)	(39.67)	(23.46)	(22.49)	(11.64)	(23.89)	(24.36)	(-4.37)	(23.22)
4	0.553***	0.530***	0.485***	0.552***	0.545***	-0.009	0.548***	0.502***	0.479***	0.441***	0.503***	0.494***	-0.008	0.497***
	(41.37)	(39.94)	(12.82)	(62.65)	(64.19)	(-0.73)	(53.72)	(22.96)	(20.97)	(11.91)	(30.11)	(31.32)	(-0.68)	(25.87)
High	0.581***	0.570***	0.522***	0.565***	0.584***	0.003	0.579***	0.533***	0.522***	0.480***	0.514***	0.535***	0.002	0.530***
	(40.43)	(40.41)	(16.10)	(24.68)	(77.47)	(0.31)	(51.21)	(26.39)	(23.01)	(14.59)	(18.31)	(31.89)	(0.25)	(25.87)
HML-B	0.046**	0.050**	-0.012	0.032*	0.142***	0.097***	0.071***	0.050***	0.051**	-0.005	0.031	0.145***	0.095***	0.072***
	(2.48)	(2.13)	(-0.42)	(1.71)	(11.07)	(4.95)	(8.01)	(2.71)	(2.16)	(-0.19)	(1.65)	(11.00)	(4.78)	(8.27)
All	0.539***	0.520***	0.519***	0.537***	0.485***	-0.054***		0.488***	0.468***	0.475***	0.488***	0.435***	-0.053***	
	(32.51)	(32.46)	(18.95)	(20.55)	(32.00)	(-5.74)		(20.34)	(17.71)	(17.30)	(18.43)	(18.51)	(-5.74)	

Table A.6 (continued)

Panel B: Monthly FF6- and DGTW-adjusted Implied Cost of Capital Sorted by Mutual Fund Ownership and ESG Ratings														
	FF6-adjusted ICC							DGTW-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel B1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.591***	0.457***	0.357***	0.534***	0.566***	-0.024**	0.566***	0.056***	0.014*	0.020**	0.030***	0.021**	-0.034***	0.030***
	(18.75)	(9.85)	(6.06)	(14.07)	(18.49)	(-2.07)	(18.55)	(6.03)	(1.67)	(2.40)	(2.84)	(2.42)	(-3.44)	(4.27)
2	0.555***	0.502***	0.435***	0.459***	0.563***	0.009	0.541***	0.033***	0.008	0.018**	0.011*	0.026***	-0.007	0.018***
	(17.44)	(12.11)	(7.43)	(10.72)	(20.16)	(0.48)	(18.02)	(2.97)	(1.01)	(2.40)	(1.72)	(3.34)	(-0.58)	(3.59)
3	0.552***	0.507***	0.485***	0.451***	0.571***	0.019	0.540***	0.035***	0.030**	0.005	0.002	0.050***	0.015	0.024***
	(16.10)	(12.07)	(10.39)	(11.15)	(19.92)	(1.19)	(17.33)	(3.53)	(2.60)	(0.69)	(0.23)	(4.09)	(1.03)	(3.80)
4	0.529***	0.478***	0.526***	0.494***	0.507***	-0.022	0.501***	0.031***	0.003	0.022***	-0.009	-0.007	-0.038***	0.004
	(14.15)	(16.20)	(16.46)	(13.57)	(15.65)	(-1.28)	(16.22)	(3.69)	(0.28)	(2.91)	(-0.95)	(-0.70)	(-2.90)	(0.54)
High	0.542***	0.471***	0.493***	0.463***	0.396***	-0.146***	0.457***	0.034***	0.022***	0.002	-0.020***	-0.071***	-0.104***	-0.024***
	(16.41)	(10.38)	(14.69)	(14.65)	(14.06)	(-11.96)	(14.69)	(3.62)	(4.13)	(0.30)	(-3.66)	(-12.37)	(-10.18)	(-6.16)
HML-G	-0.049**	0.014	0.136**	-0.070**	-0.170***	-0.122***	-0.109***	-0.022	0.008	-0.018*	-0.050***	-0.092***	-0.070***	-0.054***
	(-2.55)	(0.26)	(2.46)	(-2.22)	(-12.77)	(-7.43)	(-7.44)	(-1.63)	(0.83)	(-1.70)	(-4.20)	(-10.43)	(-4.71)	(-6.41)
All	0.527***	0.452***	0.450***	0.428***	0.425***	-0.103***		0.025***	0.011	0.014***	-0.015***	-0.049***	-0.074***	
	(15.54)	(8.87)	(8.59)	(10.34)	(14.47)	(-10.68)		(5.59)	(1.65)	(5.14)	(-2.95)	(-13.31)	(-10.65)	
Panel B2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	0.462***	0.421***	0.464***	0.415***	0.446***	-0.016	0.453***	-0.038***	-0.024***	-0.029***	-0.049***	-0.032***	0.007	-0.035***
	(14.65)	(11.35)	(16.12)	(15.19)	(15.88)	(-1.34)	(16.27)	(-3.16)	(-2.84)	(-5.34)	(-6.39)	(-4.61)	(0.59)	(-7.03)
2	0.530***	0.516***	0.450***	0.496***	0.518***	-0.012	0.517***	0.009	-0.002	-0.033***	-0.028***	-0.019**	-0.028**	-0.012*
	(27.52)	(25.98)	(14.20)	(29.11)	(36.21)	(-0.95)	(30.86)	(0.92)	(-0.25)	(-4.09)	(-3.66)	(-2.29)	(-2.29)	(-1.96)
3	0.524***	0.471***	0.479***	0.476***	0.543***	0.019*	0.513***	0.023**	-0.027	-0.021***	0.004	0.010*	-0.013	0.002
	(19.91)	(21.50)	(24.56)	(15.80)	(26.61)	(1.84)	(26.09)	(2.34)	(-1.64)	(-3.06)	(0.80)	(1.72)	(-1.18)	(0.26)
4	0.503***	0.460***	0.483***	0.462***	0.470***	-0.033	0.460***	0.032***	-0.025**	0.004	-0.015*	-0.041***	-0.073***	-0.013**
	(18.62)	(21.08)	(20.21)	(27.71)	(25.29)	(-1.22)	(24.36)	(3.01)	(-2.05)	(0.44)	(-1.97)	(-4.54)	(-5.45)	(-2.15)
High	0.477***	0.524***	0.479***	0.482***	0.394***	-0.083***	0.464***	-0.014*	0.032***	0.028***	0.003	-0.049***	-0.034***	-0.008***
	(14.71)	(25.32)	(13.68)	(19.06)	(14.30)	(-5.60)	(18.26)	(-1.74)	(5.14)	(5.01)	(0.83)	(-14.81)	(-3.36)	(-3.64)
HML-G	0.016	0.104***	0.015	0.067**	-0.051	-0.067***	0.011	0.024**	0.056***	0.057***	0.052***	-0.017**	-0.041***	0.027***
	(0.37)	(3.27)	(0.33)	(2.05)	(-1.50)	(-3.37)	(0.31)	(2.09)	(6.16)	(8.09)	(6.15)	(-2.47)	(-3.27)	(6.23)
All	0.491***	0.469***	0.471***	0.489***	0.437***	-0.053***		-0.004	-0.014**	0.015***	0.017***	-0.025***	-0.021***	
	(20.29)	(17.32)	(15.82)	(18.74)	(18.29)	(-5.52)		(-0.57)	(-2.21)	(3.54)	(3.81)	(-10.99)	(-3.01)	
Panel B3: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.450***	0.453***	0.386***	0.448***	0.391***	-0.059***	0.424***	-0.016	-0.004	-0.029***	-0.035***	-0.084***	-0.068***	-0.051***
	(12.27)	(11.20)	(8.68)	(14.49)	(14.40)	(-3.41)	(14.12)	(-1.08)	(-0.57)	(-2.95)	(-4.82)	(-16.87)	(-4.79)	(-9.25)
2	0.493***	0.493***	0.441***	0.492***	0.465***	-0.028**	0.485***	0.006	0.011	-0.003	-0.015*	-0.028***	-0.034***	-0.008
	(12.85)	(13.76)	(8.30)	(14.67)	(13.97)	(-2.48)	(13.99)	(0.46)	(1.32)	(-0.37)	(-1.79)	(-2.98)	(-3.07)	(-0.97)
3	0.526***	0.449***	0.438***	0.447***	0.506***	-0.020	0.509***	0.012	0.004	-0.008	-0.017*	-0.003	-0.016	0.000
	(13.97)	(9.12)	(8.31)	(11.19)	(16.42)	(-1.62)	(15.69)	(1.34)	(0.43)	(-1.12)	(-1.69)	(-0.51)	(-1.46)	(0.02)
4	0.555***	0.537***	0.483***	0.497***	0.571***	0.015	0.541***	0.038***	0.018**	0.004	0.013**	0.038***	-0.000	0.025***
	(18.25)	(20.39)	(14.33)	(13.50)	(21.76)	(1.20)	(19.10)	(4.07)	(2.41)	(0.41)	(2.52)	(4.38)	(-0.01)	(3.88)
High	0.585***	0.548***	0.515***	0.563***	0.578***	-0.006	0.564***	0.062***	0.030***	0.018*	0.042***	0.037***	-0.025***	0.038***
	(19.62)	(17.45)	(14.89)	(17.30)	(19.66)	(-0.87)	(18.54)	(5.69)	(2.83)	(1.71)	(3.77)	(3.54)	(-3.75)	(3.91)
HML-B	0.135***	0.095***	0.129***	0.115***	0.188***	0.053***	0.140***	0.078***	0.035**	0.047***	0.077***	0.121***	0.044***	0.090***
	(5.24)	(2.62)	(2.77)	(6.46)	(10.75)	(3.10)	(7.91)	(3.46)	(2.56)	(3.08)	(5.85)	(10.20)	(2.96)	(6.60)
All	0.527***	0.452***	0.450***	0.428***	0.425***	-0.103***		0.025***	0.011	0.014***	-0.015***	-0.049***	-0.074***	
	(15.54)	(8.87)	(8.59)	(10.34)	(14.47)	(-10.68)		(5.59)	(1.65)	(5.14)	(-2.95)	(-13.31)	(-10.65)	
Panel B4: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2021)														
Low	0.484***	0.473***	0.490***	0.484***	0.394***	-0.091***	0.460***	0.004	0.024***	0.026***	0.003	-0.048***	-0.052***	-0.007***
	(15.45)	(15.13)	(19.18)	(21.74)	(14.29)	(-6.64)	(19.39)	(0.41)	(5.12)	(3.88)	(1.01)	(-14.18)	(-5.20)	(-5.15)
2	0.471***	0.486***	0.479***	0.479***	0.493***	0.021	0.488***	-0.004	-0.011*	0.008	-0.010	-0.014**	-0.010	-0.009*
	(21.11)	(20.69)	(17.53)	(25.37)	(25.52)	(1.56)	(25.86)	(-0.41)	(-1.87)	(0.85)	(-1.35)	(-1.99)	(-0.91)	(-1.89)
3	0.500***	0.463***	0.434***	0.457***	0.453***	-0.047***	0.470***	-0.008	-0.047***	-0.030***	-0.043***	-0.050***	-0.042***	-0.038***
	(23.21)	(22.10)	(11.36)	(23.64)	(23.32)	(-4.48)	(22.53)	(-1.01)	(-7.88)	(-4.22)	(-8.25)	(-7.30)	(-3.48)	(-10.56)
4	0.504***	0.481***	0.441***	0.503***	0.494***	-0.010	0.498***	-0.001	-0.033***	-0.023***	-0.020***	-0.023***	-0.022**	-0.020***
	(22.49)	(20.58)	(11.96)	(29.45)	(30.14)	(-0.85)	(25.09)	(-0.15)	(-4.42)	(-4.20)	(-4.67)	(-4.34)	(-2.37)	(-4.84)
High	0.534***	0.521***	0.475***	0.520***	0.534***	0.000	0.530***	-0.006	0.002	-0.009	0.008*	0.008	0.014	0.001
	(25.58)	(22.63)	(13.46)	(20.23)	(31.81)	(0.03)	(25.32)	(-0.68)	(0.37)	(-1.19)	(1.71)	(1.23)	(1.57)	(0.14)
HML-B	0.050***	0.048**	-0.015	0.036**	0.141***	0.091***	0.070***	-0.010	-0.022***	-0.035***	0.005	0.056***	0.066***	0.007*
	(2.82)	(2.07)	(-0.60)	(2.10)	(10.90)	(4.75)	(8.30)	(-0.62)	(-3.00)	(-3.36)	(0.91)	(7.66)	(4.47)	(1.74)
All	0.491***	0.469***	0.471***	0.489***	0.437***	-0.053***		-0.004	-0.014**	0.015***	0.017***	-0.025***	-0.021***	
	(20.29)	(17.32)	(15.82)	(18.74)	(18.29)	(-5.52)		(-0.57)	(-2.21)	(3.54)	(3.81)	(-10.99)	(-3.01)	

Figure A.1: Characteristics of the Marginal Fund: Calibration

This figure shows the characteristics of the optimal information acquisition and the portfolio policy of an infinitely small agent in an economy where two masses of agents coexist: ESG indifferent and ESG perceptive. The ESG preference of the marginal agent δ_j is allowed to vary. Graphs (a) to (h) show the optimal signal precision, the total cost of information acquisition, the expected difference in the portfolio positions relative to the market, the expected nonpecuniary benefits of the portfolio, the expected dispersion of the portfolio positions, the tracking error, the expected net payoff, and the CAPM alpha of the portfolio. Graph (i) shows the certainty equivalent loss, relative to the expected net payoff, that is perceived by the marginal agent when forced to acquire the information and implement the conditional portfolio of an agent with ESG preferences δ_{sub}.

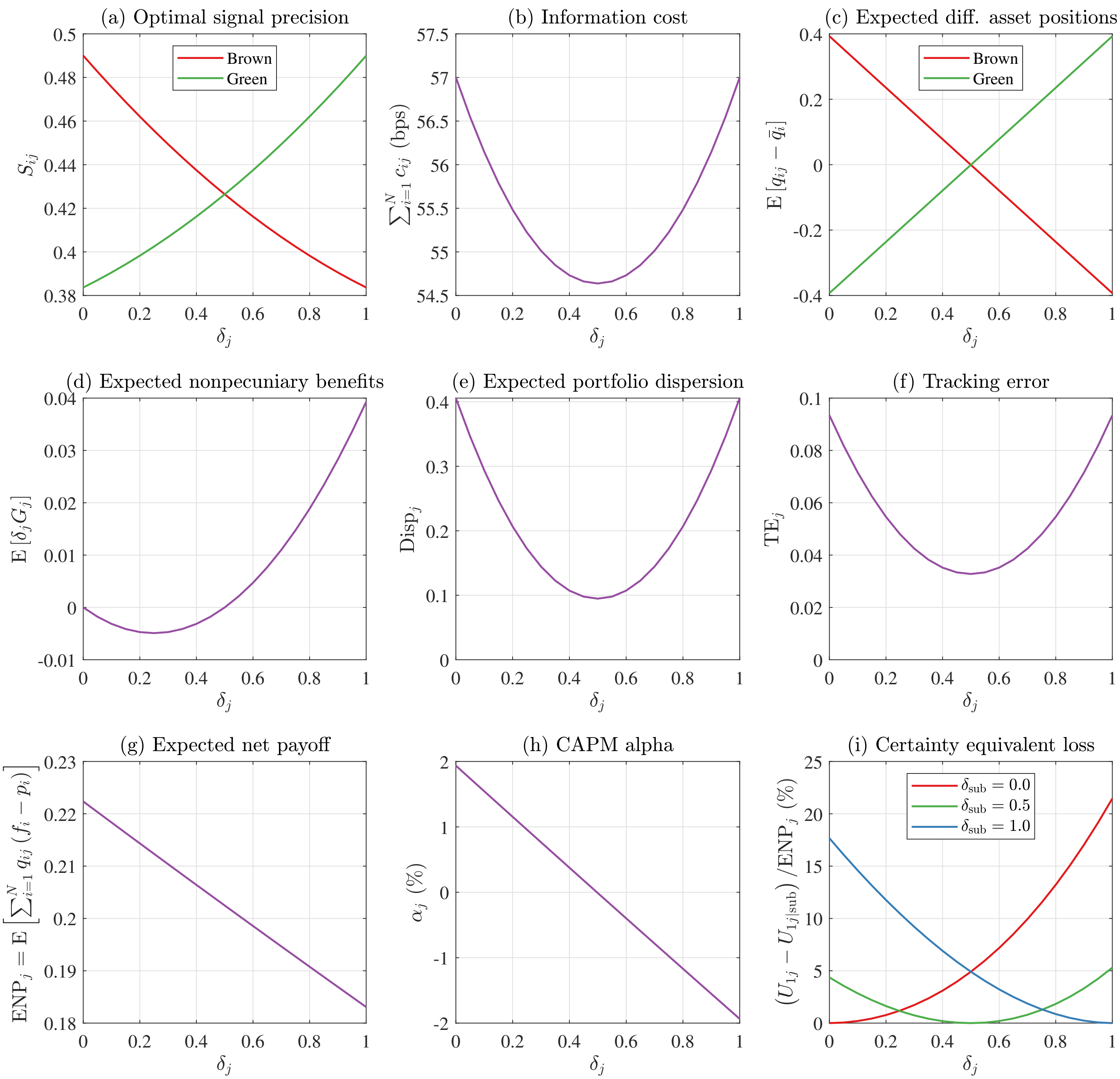

Figure A.2: Equilibrium Asset Pricing: Calibration

Graphs (a) show the equilibrium aggregate signal precision for the green and brown assets in the economy. Graphs (b) show the price informativeness of the assets. Graphs (c) show the aggregate information acquisition cost. ESG-perceptive funds have ESG preferences of δ_P and represent a fraction φ of the total population, while ESG-indifferent funds have zero ESG preferences ($\delta_I = 0$). For the graphs in the top row, δ_P varies between 0 and 2, while $\varphi = 0.5$. For the graphs in the bottom row, $\delta_P = 1$, while φ varies between 0 and 1.

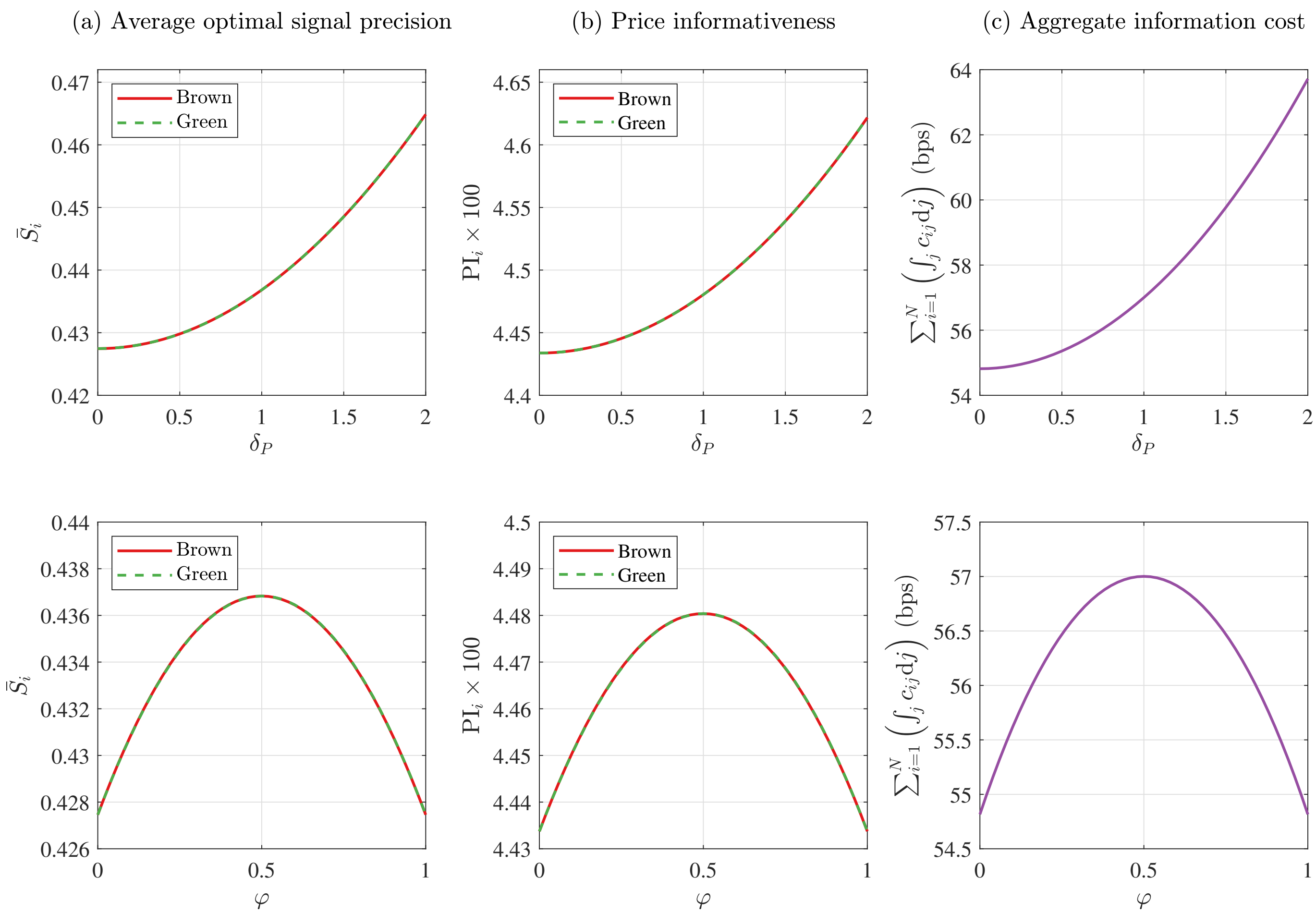

Figure A.3: Implied Cost of Capital of Portfolios Sorted by ESG Rating: Composite ICC Measure

In Graph (a), at the end of month t, stocks are sorted into quintiles according to their ESG ratings, with Quintile 1 (Quintile 5) comprising the bottom (top) quintile of stocks based on the ESG rating. For each of the five portfolios, we compute the value-weighted implied cost of capital (ICC) in month $t+1$ and rebalance the portfolios at the end of month $t+1$. We employ the composite of the mechanical-based ICCs for each stock-month following Lee et al. (2021), and plot the time-series averages of the monthly ICCs for each of the five portfolios, as well as the Newey-West adjusted 95% confidence intervals. Graphs (b) to (d) plot the CAPM-adjusted ICCs, Fama-French six-factor-adjusted ICCs (FF6) and characteristic-adjusted ICCs per Daniel et al. (1997) (DGTW).